

# Signals 2: Sampling & Interpolation

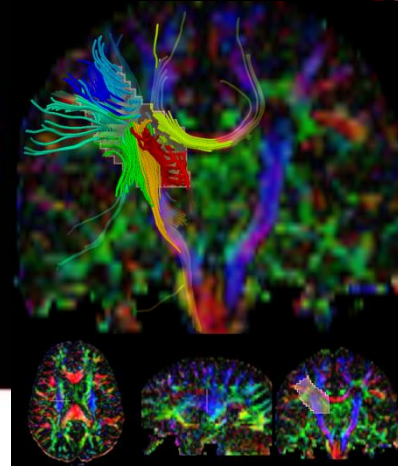
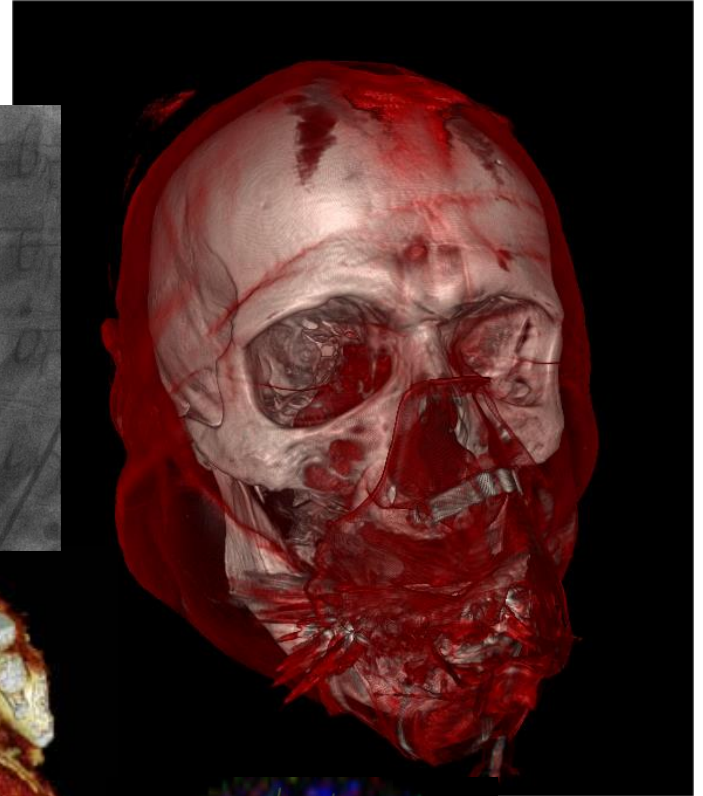
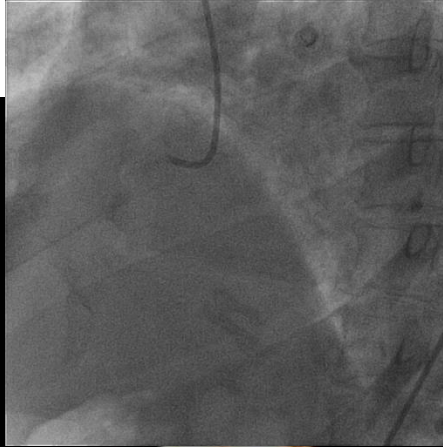
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2020-09-14

# Philips Healthcare



# Produces images



# Basics

(stuff you already should know)

# Dirac impulse $\delta$

- Also known as: Dirac delta, delta function, Dirac delta function, Dirac operator

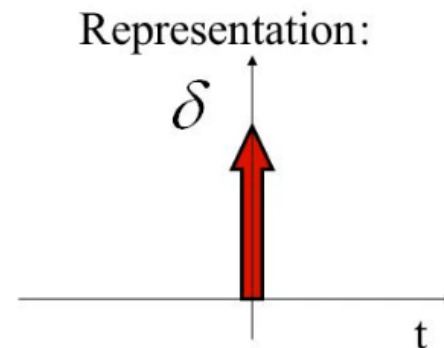
## Dirac delta function $\delta(t)$

- This “unit impulse” function is defined by the conditions:

$$\delta(t) = 0, \text{ for } t \neq 0.$$

$$\delta(0) = +\infty$$

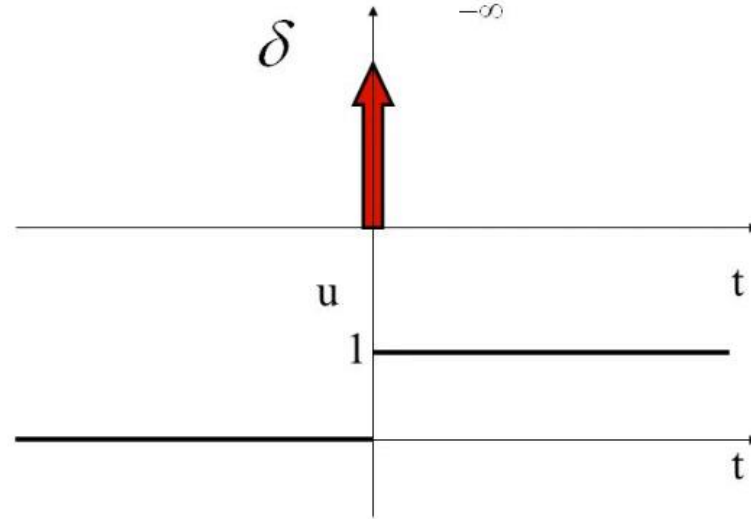
$$\int_{-\infty}^{+\infty} \delta(t) dt = 1$$



# Dirac impulse $\delta$

- Integral of the Dirac function:

Calculate:  $u(t) = \int_{-\infty}^t \delta(\sigma) d\sigma$

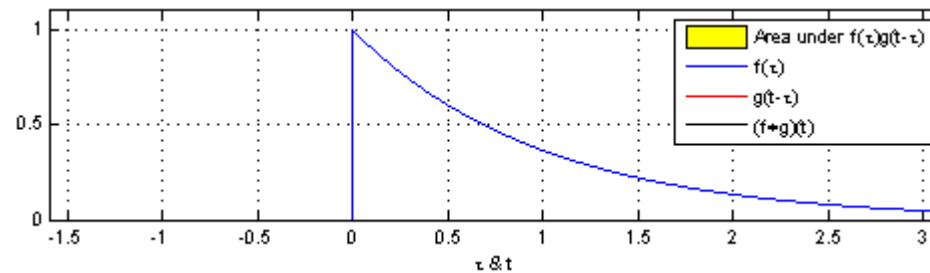
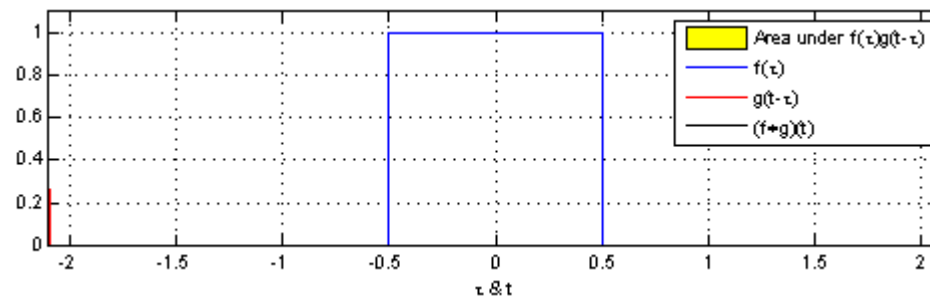


$$u(t) = \begin{cases} 0 & \text{if } t < 0 \\ 1 & \text{if } t > 0 \end{cases}$$

Remark: value at  $t = 0$  is not well defined, we adopt one by convention.

# Convolution integral

$$y(t) = f(t) * h(t) = \int_{-\infty}^{\infty} f(\tau) h(t - \tau) d\tau$$



# Convolution integral

$$y(t) = f(t) * h(t) = \int_{-\infty}^{\infty} f(\tau) h(t - \tau) d\tau$$

- Time and frequency domain:
  - Convolution in time domain  $f(t) * h(t)$  -> multiplication in frequency domain  $F(\omega) \cdot H(\omega)$
  - Multiplication in time domain  $f(t) \cdot h(t)$  -> convolution in frequency domain  $F(\omega) * H(\omega)$



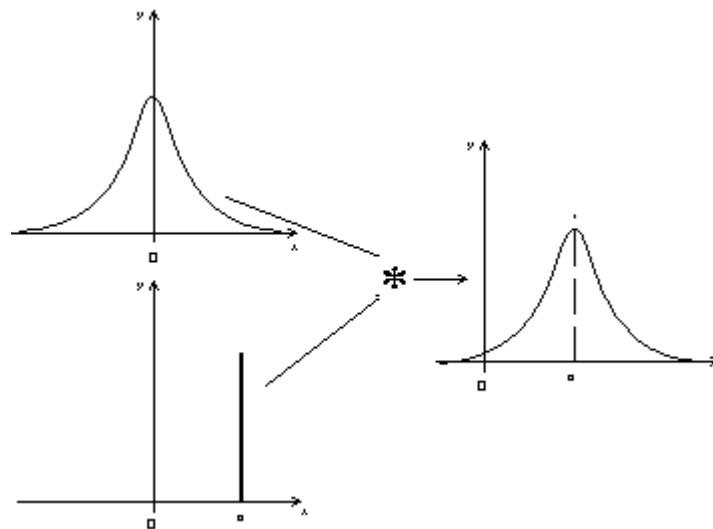
# Convolution with the Dirac function

$$y(t) = \delta(t) * h(t) = \int_{-\infty}^{\infty} \delta(\tau) h(t - \tau) d\tau = h(t)$$



# Convolution with a shifted Dirac function

$$y(t) = \delta(t - s) * h(t) = \int_{-\infty}^{\infty} \delta(\tau - s) h(t - \tau) d\tau = h(t - s)$$



# Fourier Transform

- Fourier Transform

$$F(\omega) = \int_{-\infty}^{\infty} f(t) e^{-i\omega t} dt$$

$$e^{-i\omega t} = \cos(\omega t) - i \sin(\omega t)$$

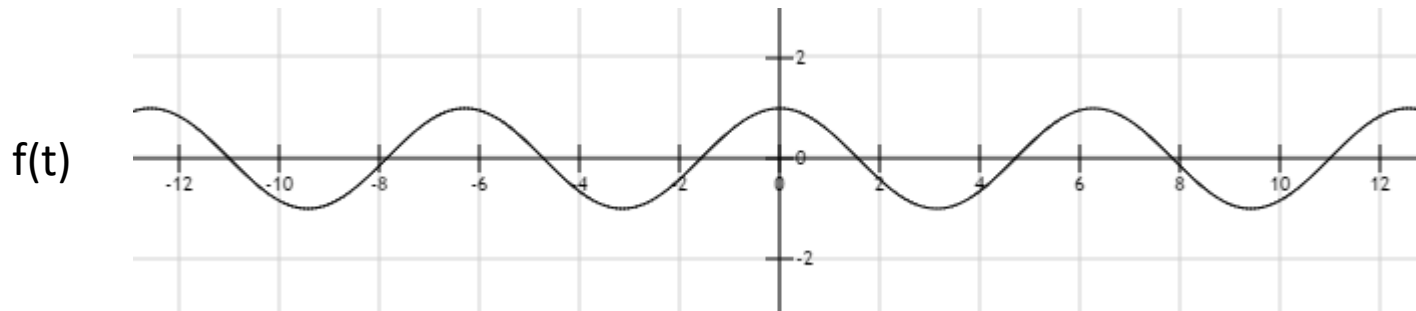
- Inverse Fourier Transform

$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(\omega) e^{i\omega t} d\omega$$

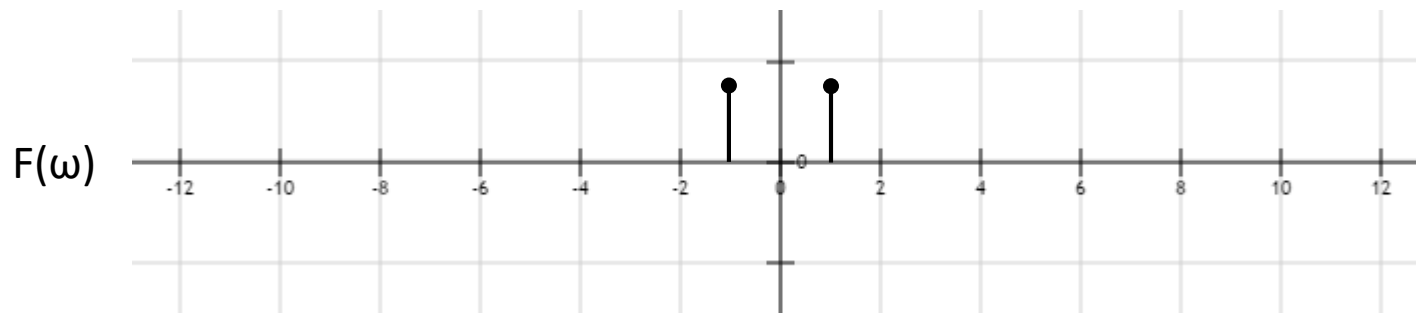
$$\omega = 2\pi f$$

# Fourier Transform

## Cosine wave



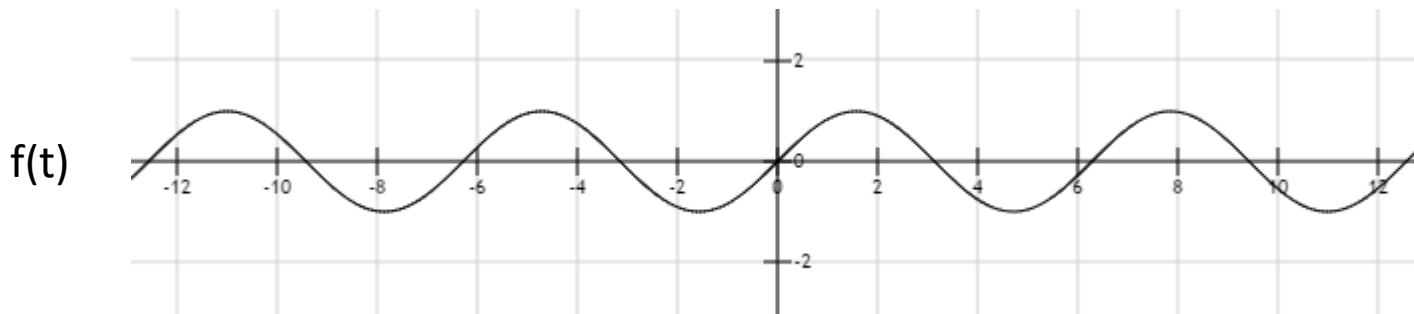
$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(\omega) e^{i\omega t} d\omega$$



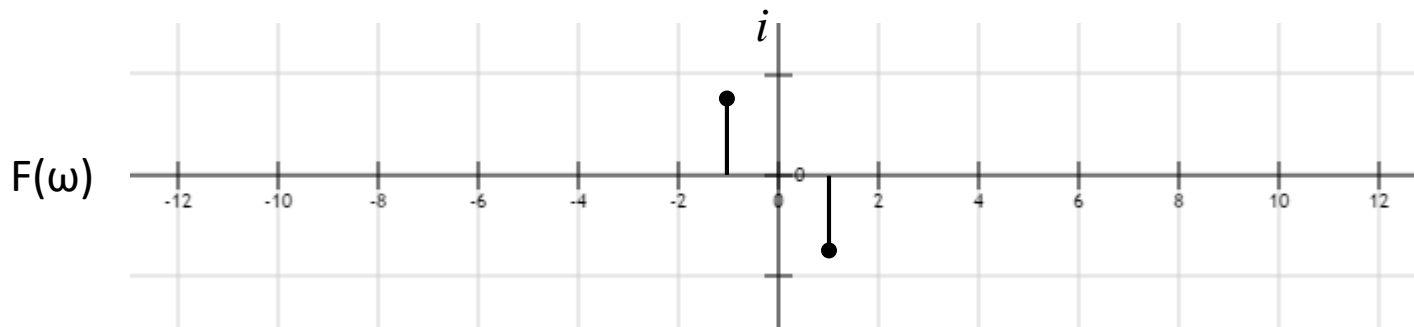
$$e^{-i\omega t} = \cos(\omega t) - i \sin(\omega t)$$

# Fourier Transform

Sine wave



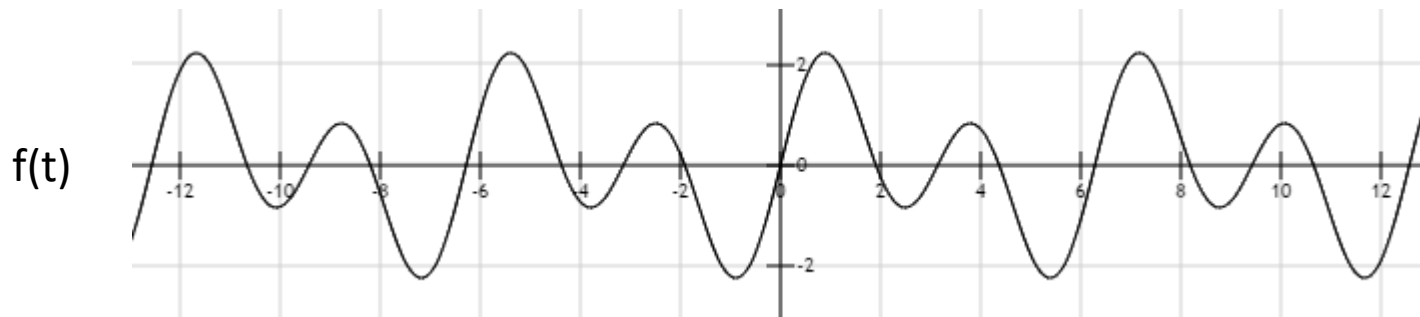
$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(\omega) e^{i\omega t} d\omega$$



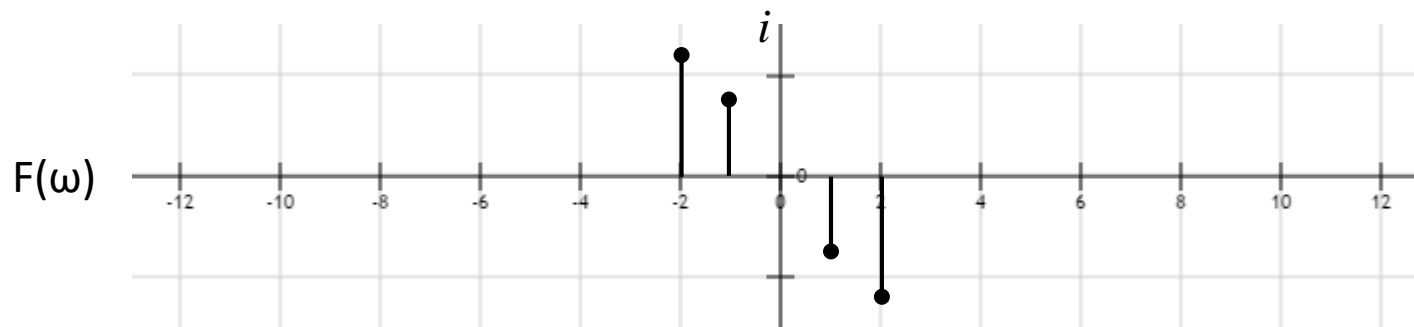
$$e^{-i\omega t} = \cos(\omega t) - i \sin(\omega t)$$

# Fourier Transform

$$\sin(t) + 1.5 * \sin(2t)$$

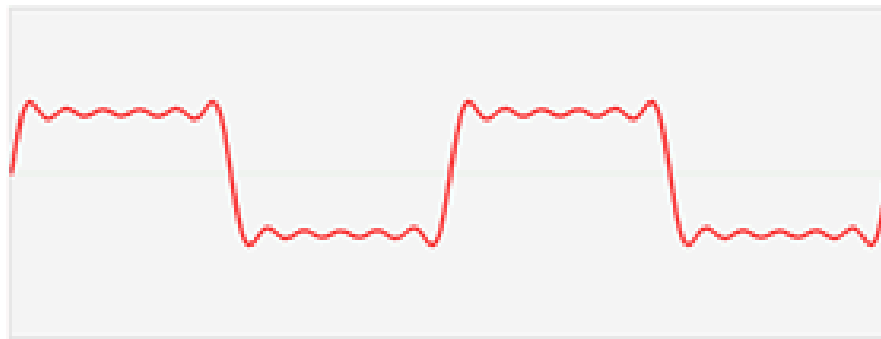


$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(\omega) e^{i\omega t} d\omega$$



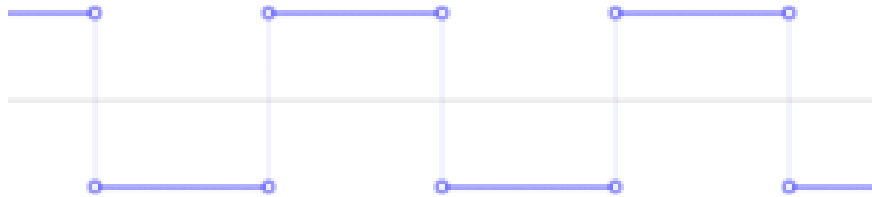
# Periodic square (rect, box) function

Approximated by 6 Fourier components

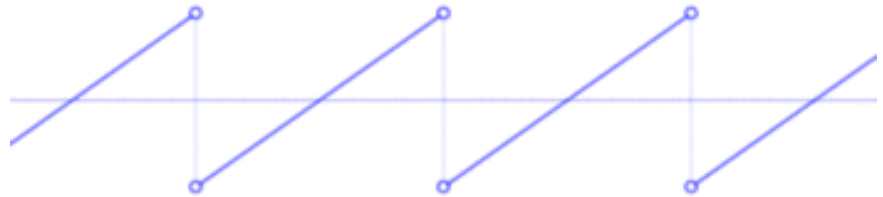


# Approximating by Fourier series

Square wave and saw tooth



$N = 0$



$N = 0$

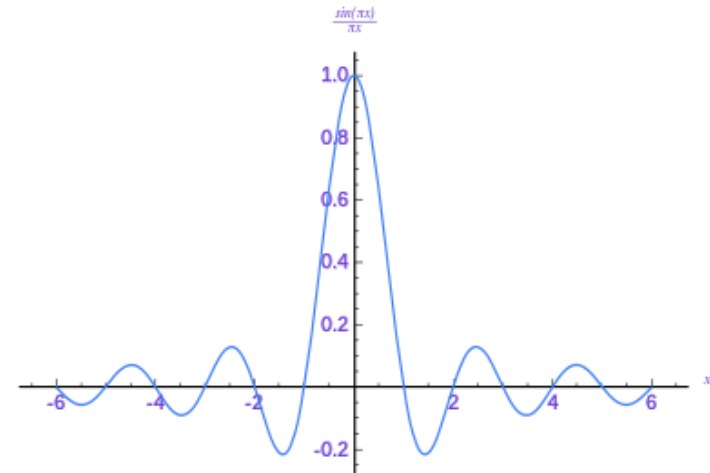
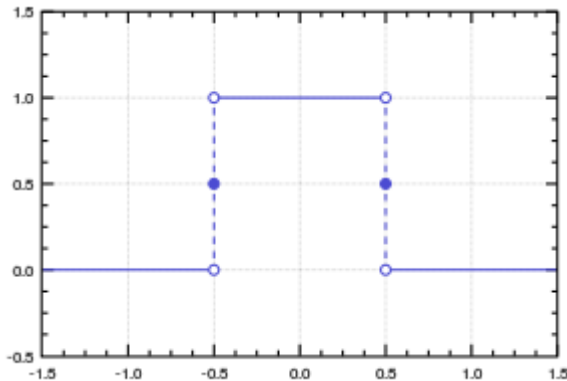


# Playground

- <http://bl.ocks.org/jinroh/7524988>

# Fourier transform of a square

rect function, box function

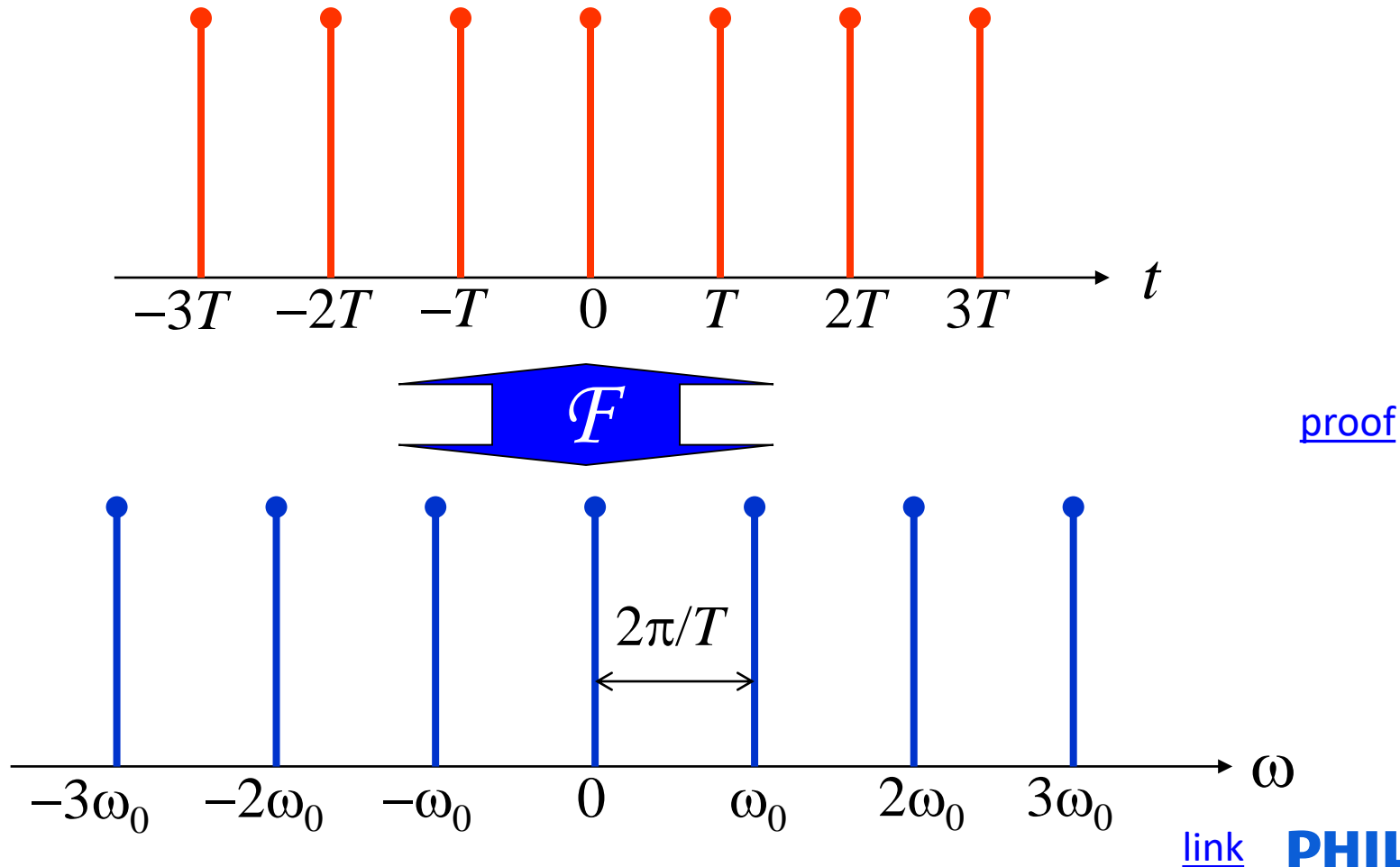


$$\int_{-\infty}^{\infty} \text{rect}(t) \cdot e^{-i2\pi ft} dt = \frac{\sin(\pi f)}{\pi f} = \text{sinc}(\pi f)$$

# Sampling

# Dirac train, pulse train

Also known as: impulse train, pulse train, Dirac comb



# Pulse train example

- \* Fourier Transform Continuous time signals (FTC)

$$X(\omega) = \int_{-\infty}^{\infty} x(t) e^{-j\omega t} dt \quad \longleftrightarrow \quad \frac{1}{2\pi} \int_{-\infty}^{\infty} X(\omega) e^{j\omega t} d\omega$$

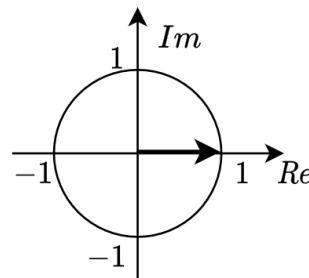
- \* Let us look at an example of an FTC pair: pulse train

$$s(t) = \sum_{n=-\infty}^{\infty} \delta(t - n \cdot T) \quad \longleftrightarrow \quad S(\omega) = \sum_{n=-\infty}^{\infty} e^{-j\omega n T}$$

- \* What will a pulse train look like in frequency domain?
- \* Look at  $S(\omega)$ , what happens when  $\omega = 0$ ?

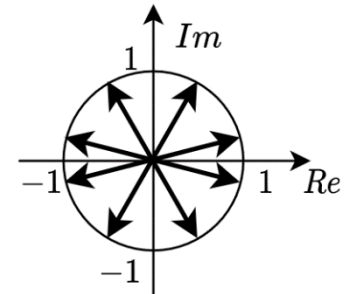
# Pulse train example

- \*  $S(\omega) = \sum_{n=-\infty}^{\infty} e^{-j\omega nT}$
- \* Look at  $S(\omega)$ , what happens when  $\omega = 0$ ?
- \* The phasor will be 1 and the sum goes to infinity
- \*  $S(0) = \sum_{n=-\infty}^{\infty} e^{-j \cdot 0 \cdot nT} = \sum_{n=-\infty}^{\infty} 1$
- \* Now what happens when  $\omega$  is slightly larger than 0?



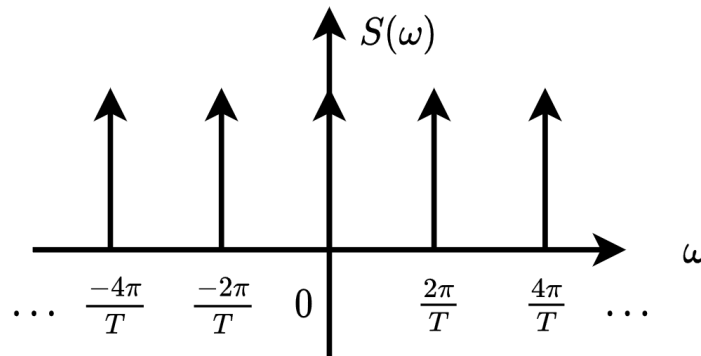
# Pulse train example

- \* Now what happens when  $\omega$  is slightly larger than 0?
- \*  $S(\omega) = \sum_{n=-\infty}^{\infty} (e^{-j\omega T})^n$
- \* An infinite amount of phasors will rotate around the unit circle, but for each phasor there is another phasor that is shifted with exactly  $\pi$
- \* These phasors will cancel each other out, summing to 0
- \*  $S(\omega) = \sum_{n=-\infty}^{\infty} (e^{-j\omega T})^n = 0$ , with  $0 < \omega < \frac{2\pi}{T}$
- \* Now what happens if  $\omega = \frac{2\pi}{T}$ ?



# Pulse train example

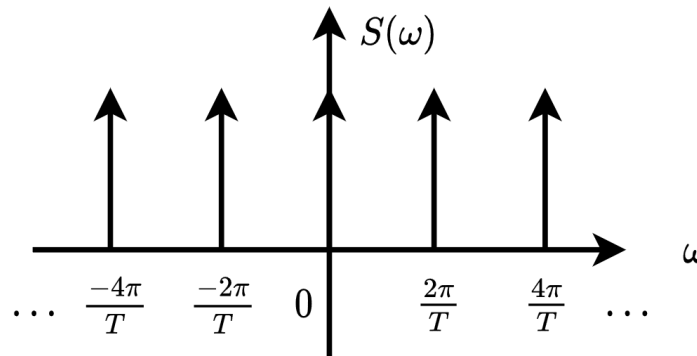
- \* Now what happens if  $\omega = \frac{2\pi}{T}$ ?
- \*  $S\left(\frac{2\pi}{T}\right) = \sum_{n=-\infty}^{\infty} (e^{-j\frac{2\pi}{T}T})^n = \sum_{n=-\infty}^{\infty} (e^{-j2\pi})^n = \sum_{n=-\infty}^{\infty} 1 = S(0)$
- \* In frequency domain, a pulse train will be a pulse train of infinitely high and infinitely narrow pulses spaced  $\frac{2\pi}{T}$  apart



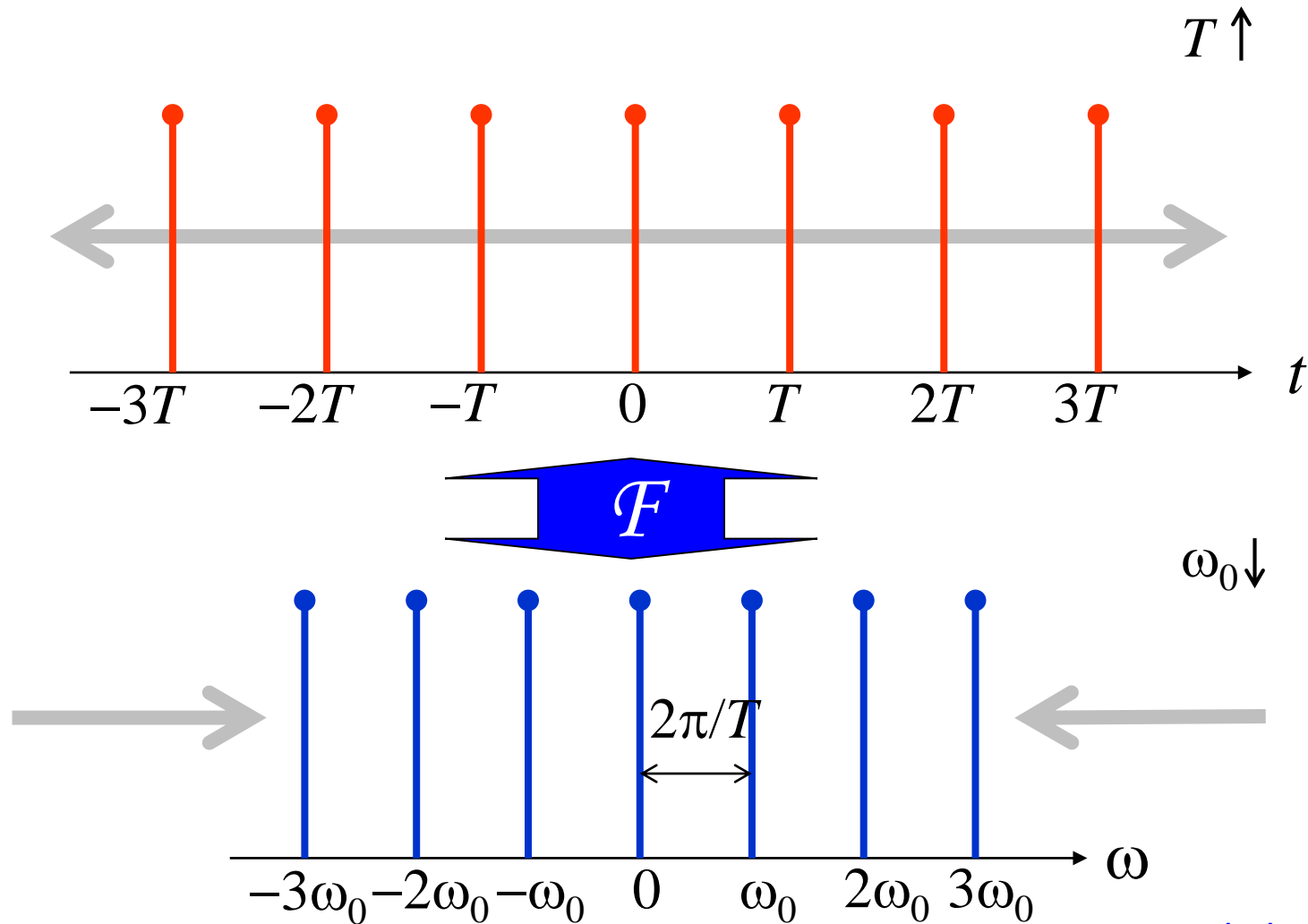


# Pulse train example

- \* Note that in the time domain the pulses of a pulse train are a distance  $T$  apart, but in the frequency domain they are a distance  $\frac{2\pi}{T}$  apart
- \* This means that if we lower the sample frequency, the time domain pulses will move further apart, but the frequency domain pulses move closer together

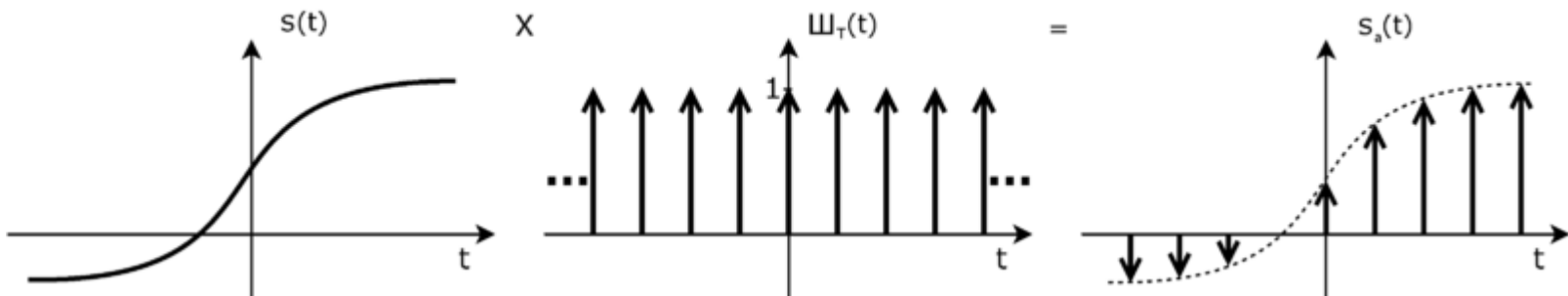


# Dirac train, pulse train



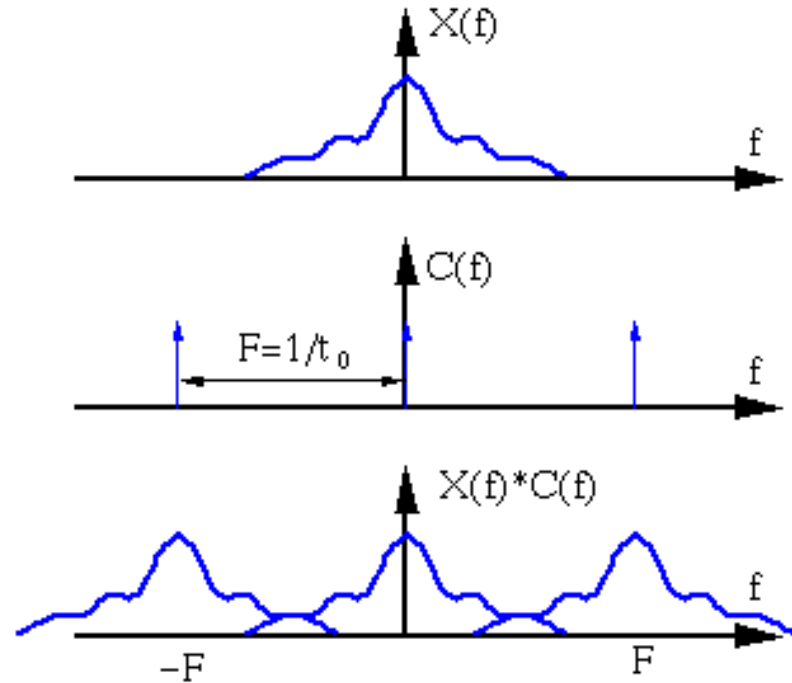
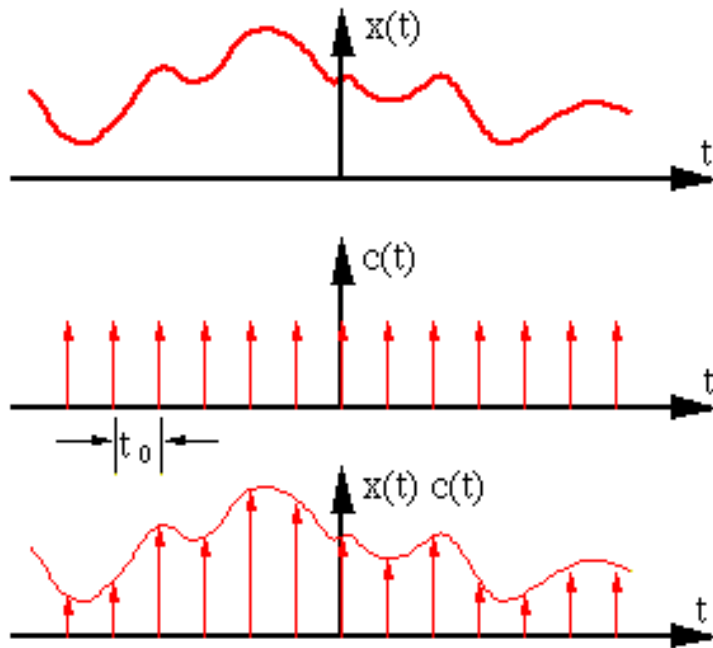
# Sampling

= multiplication with Dirac train



# Sampling

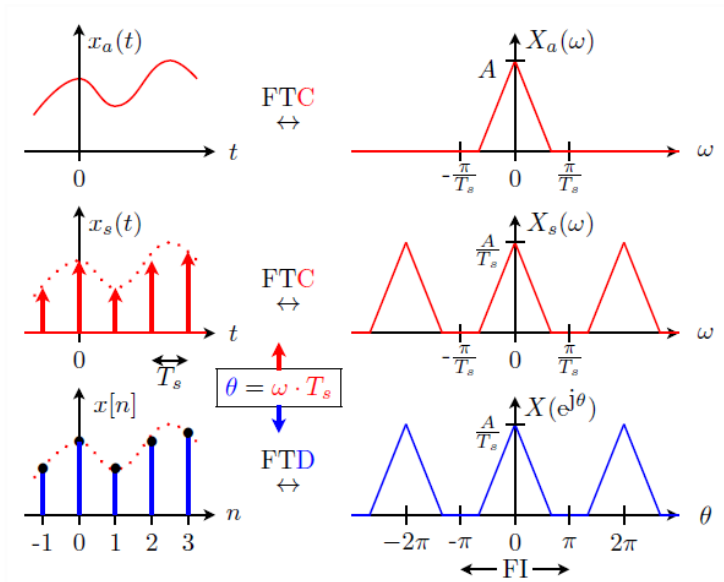
## Fourier space



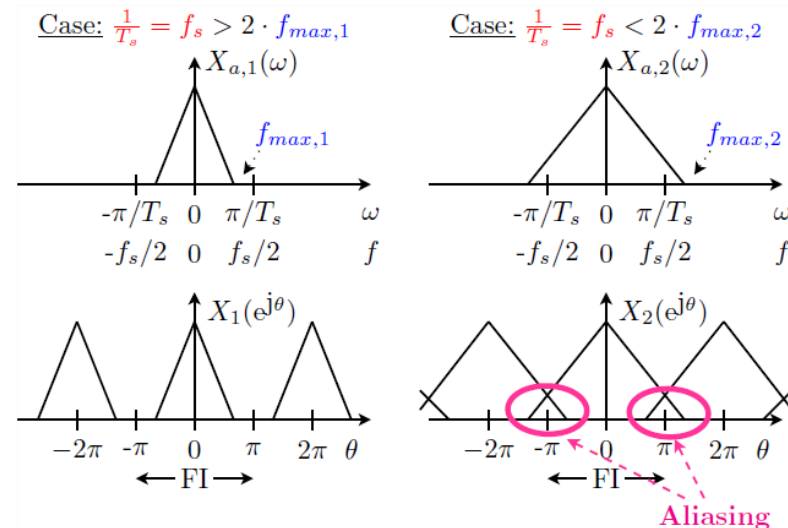
Nyquist criterion:  $f > 2 \cdot f_{\max}$

# Shannon theorem

### C-to-D:



## Aliasing:

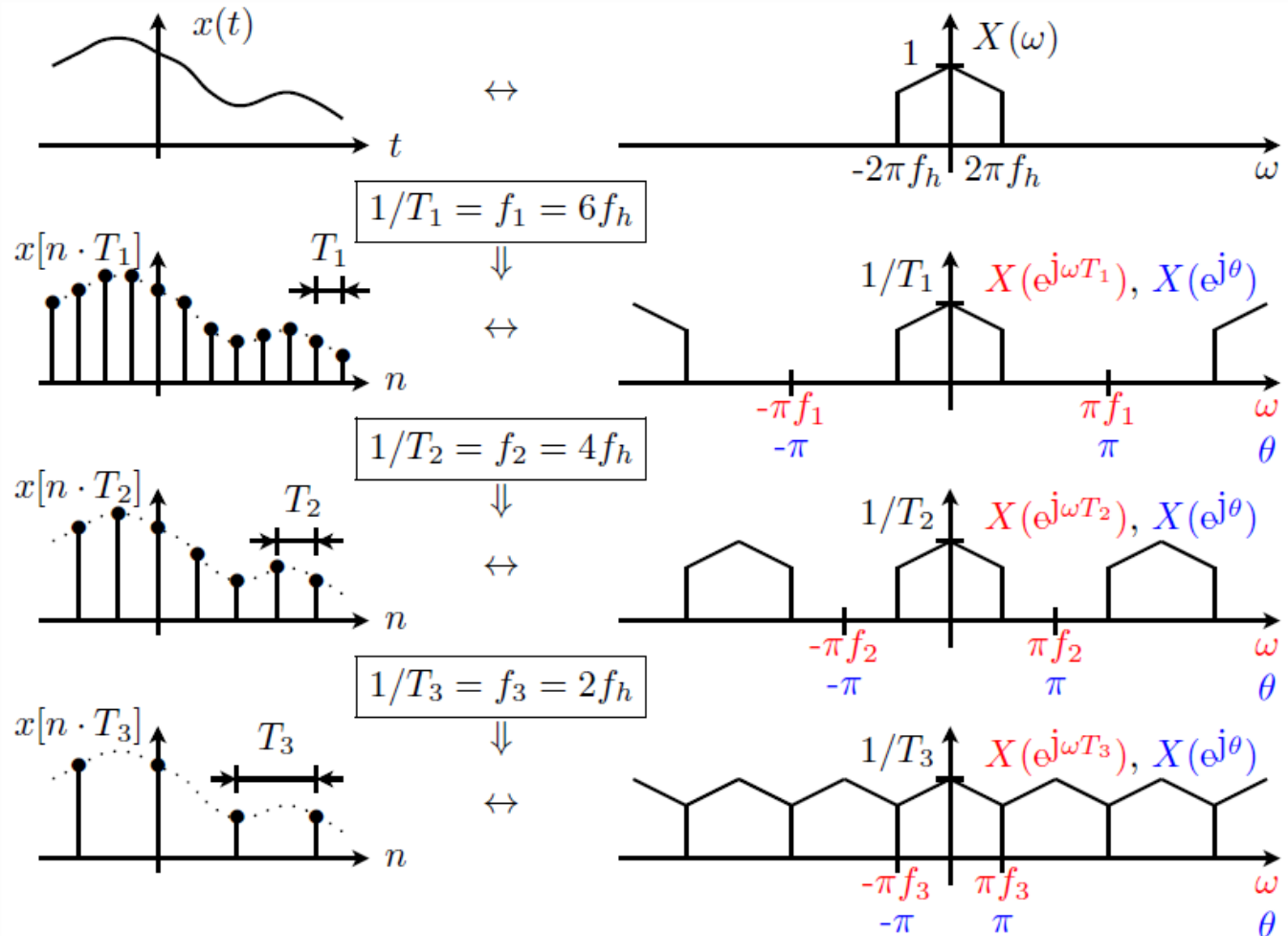


# Shannon Sampling Theorem

Continuous-time signal  $x_a(t)$  with frequencies no higher than  $f_{max}$  can be reconstructed exactly from its samples  $x[n] = x_a(t)|_{t=n \cdot T_s}$ , if samples are taken at a rate  $f_s = 1/T_s$ , that is greater than  $2f_{max}$

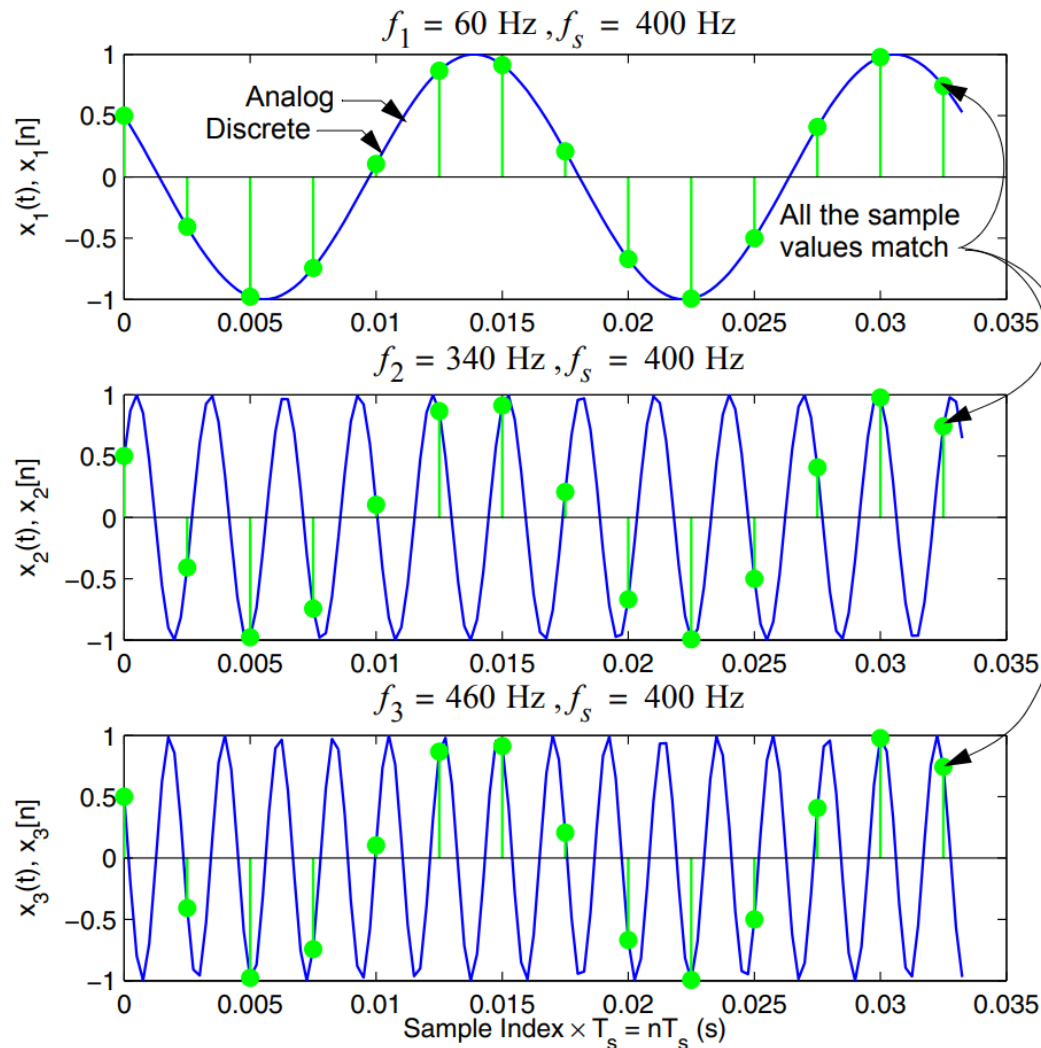
# Sampling rate

What happens if we change sample rate?



# Sampling rate & Nyquist frequency

[link](#)



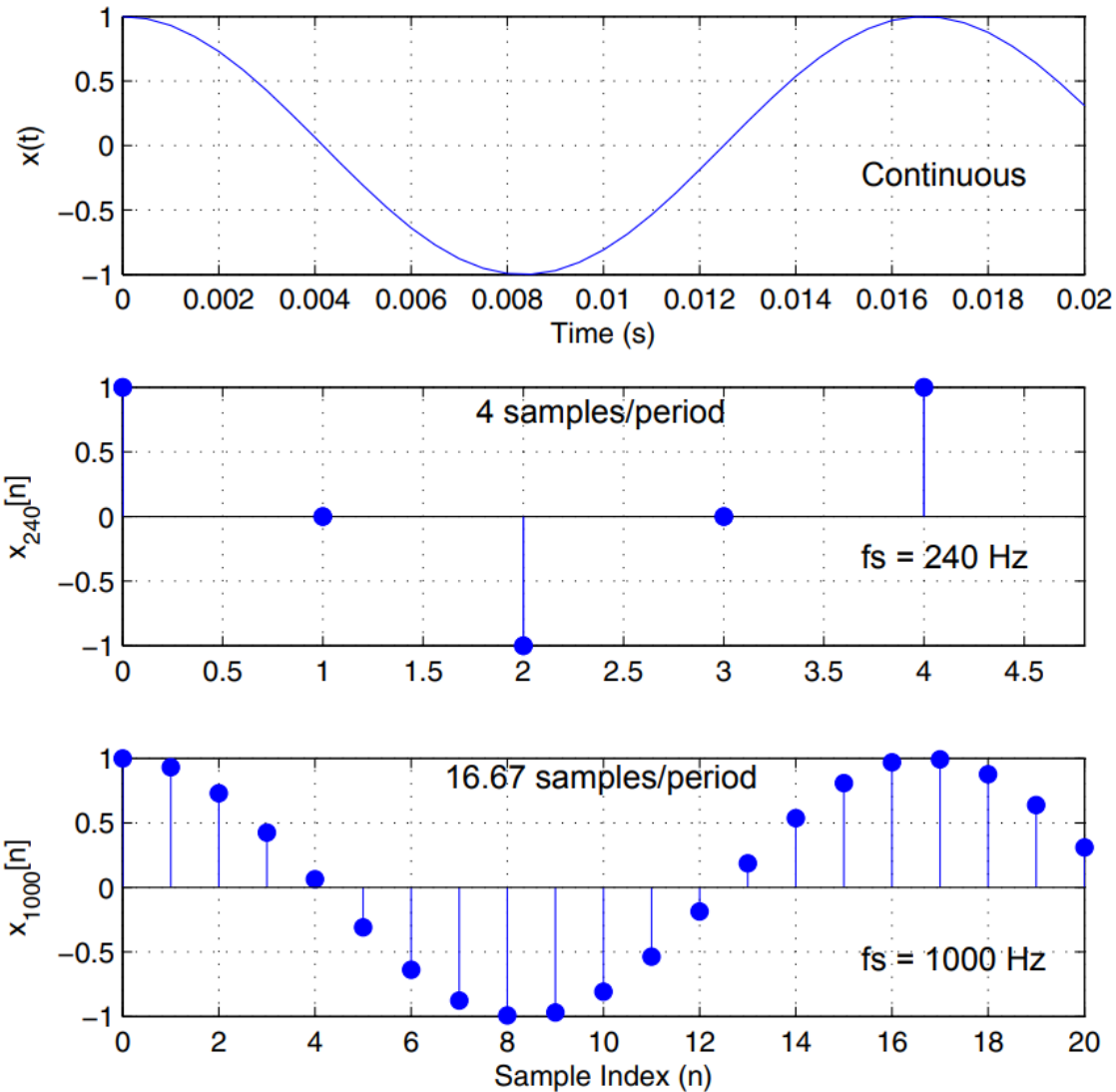
$$x_1(t) = \cos(2\pi \cdot 60 \cdot t + \pi/3)$$

$$x_2(t) = \cos(2\pi \cdot 340 \cdot t - \pi/3)$$

$$x_3(t) = \cos(2\pi \cdot 460 \cdot t + \pi/3)$$

# Sampling rate & Nyquist frequency

[link](#)



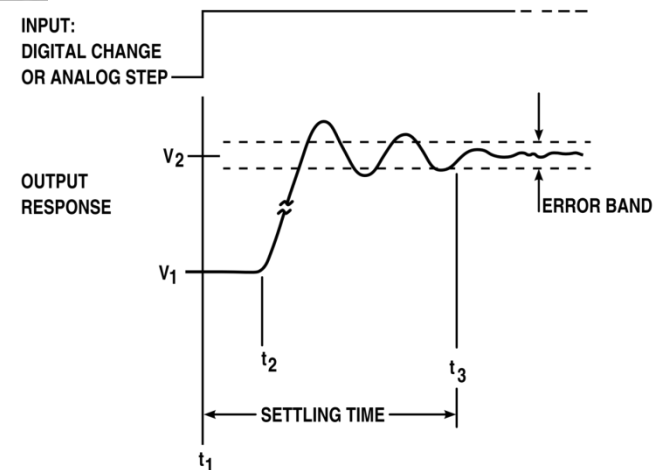
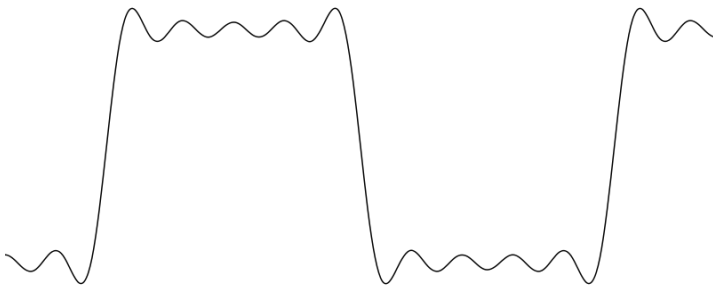


# Playground

- <http://rest-term.com/labs/html5/fft.html>

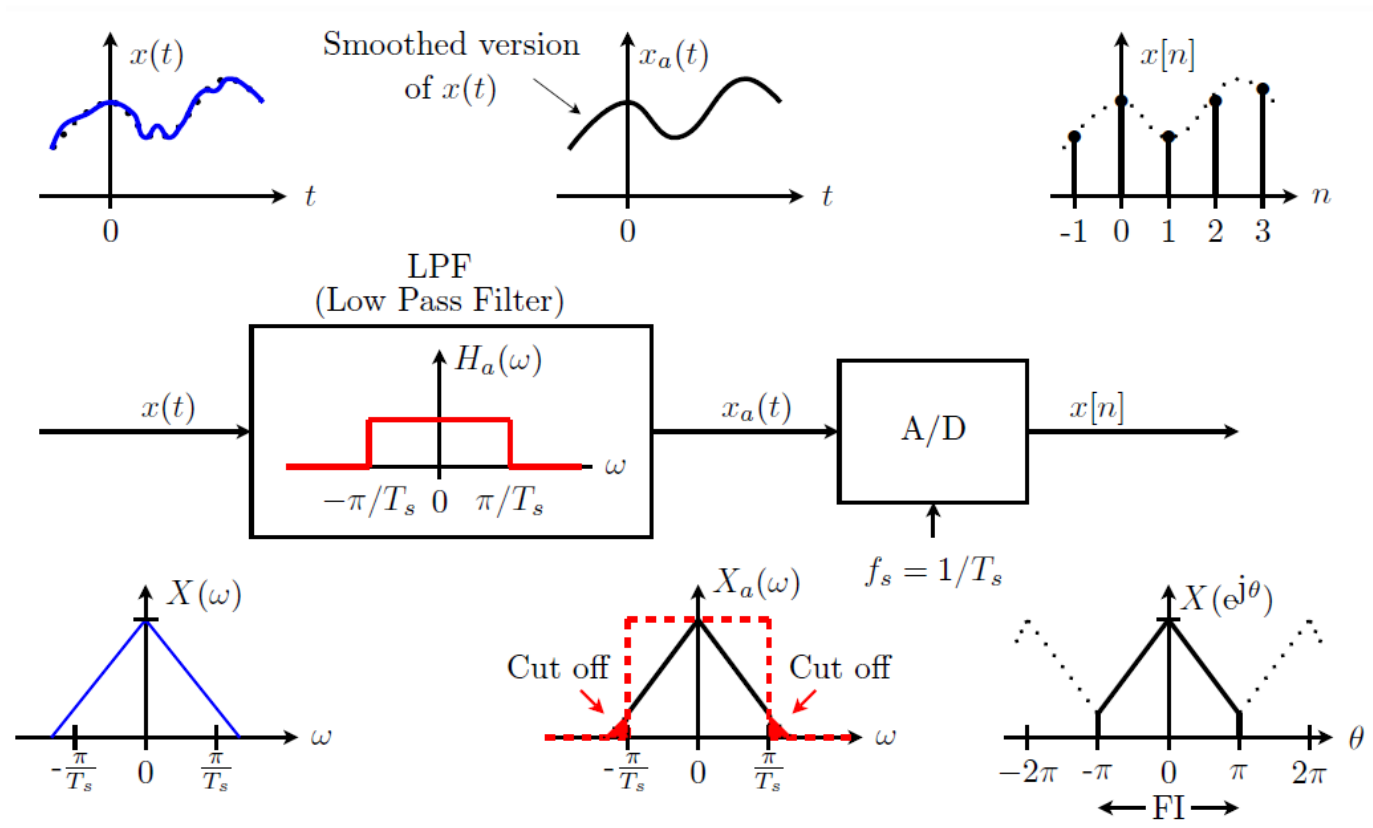
# “Ideal sampling”

Not so ideal for non-bandwidth limited signals



# Sampling of natural signals

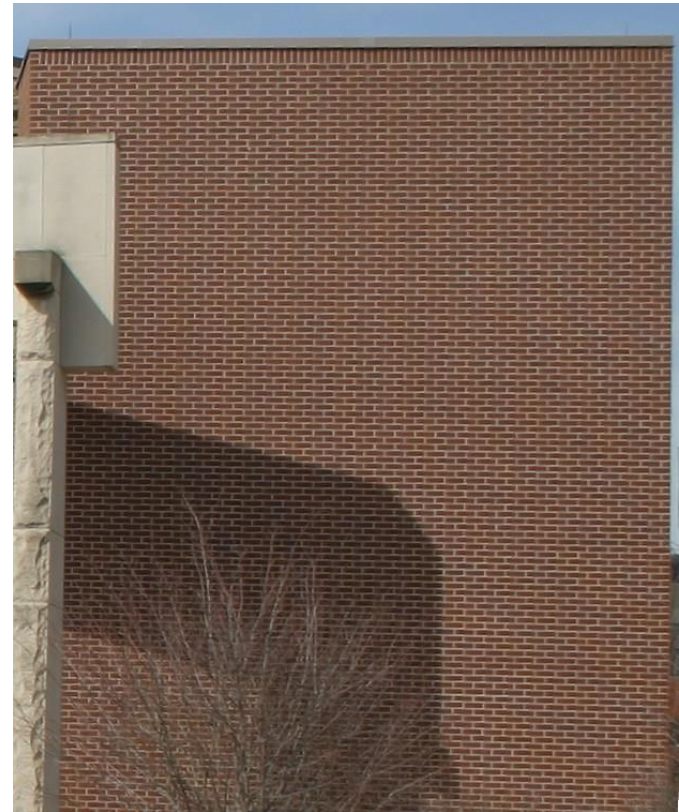
Not bandwidth limited signals



# Aliasing, low pass filter

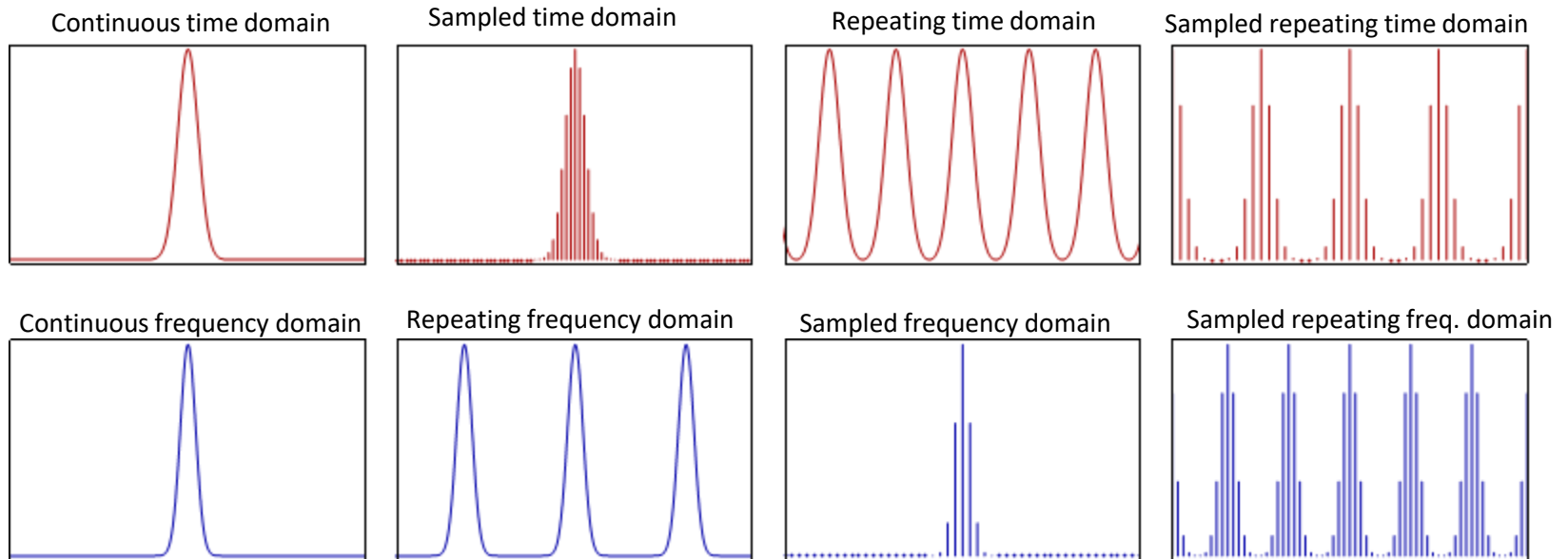


Without low pass



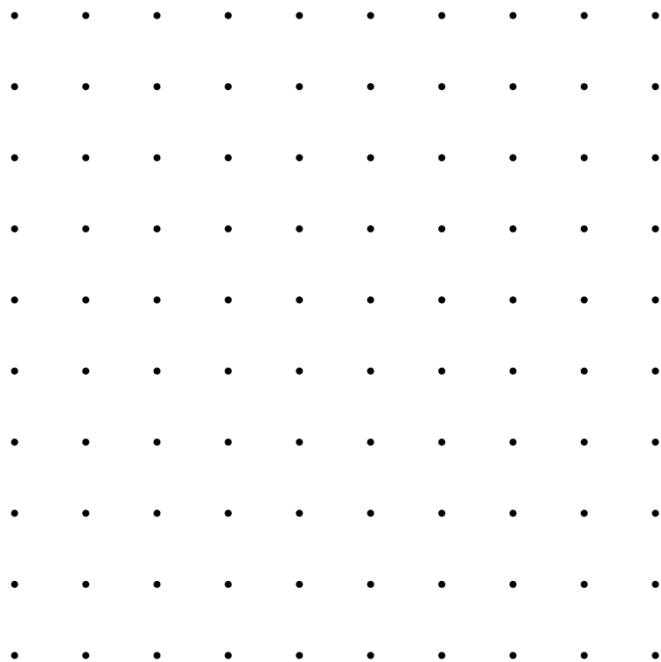
With low pass

# Discrete Fourier Transform

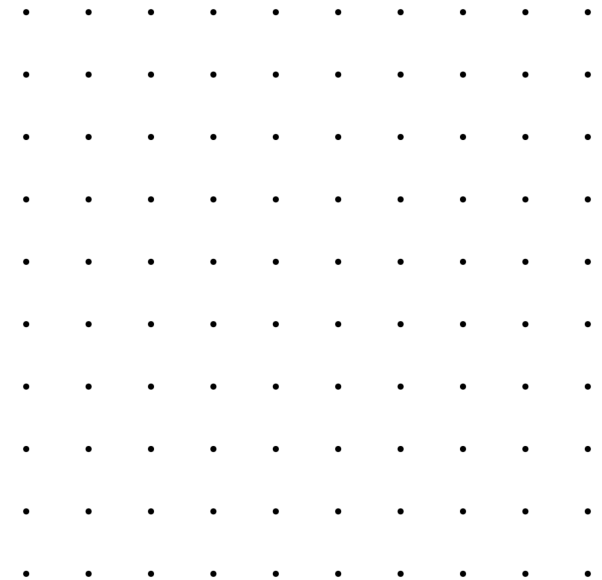


# Sampling in higher dimensions

2D, 3D



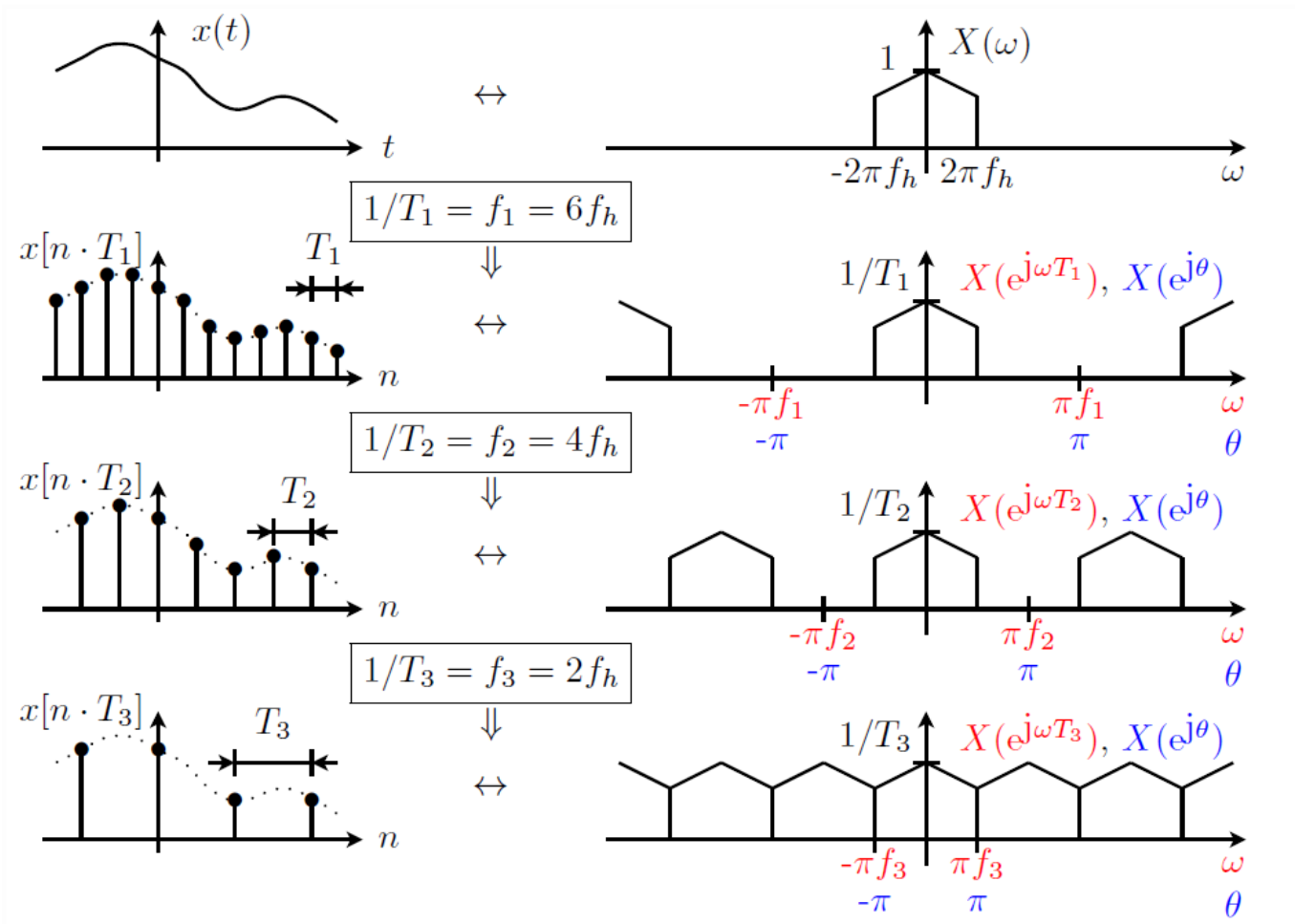
Fourier  
transform



# Sample rate conversion

# Sample rate conversion

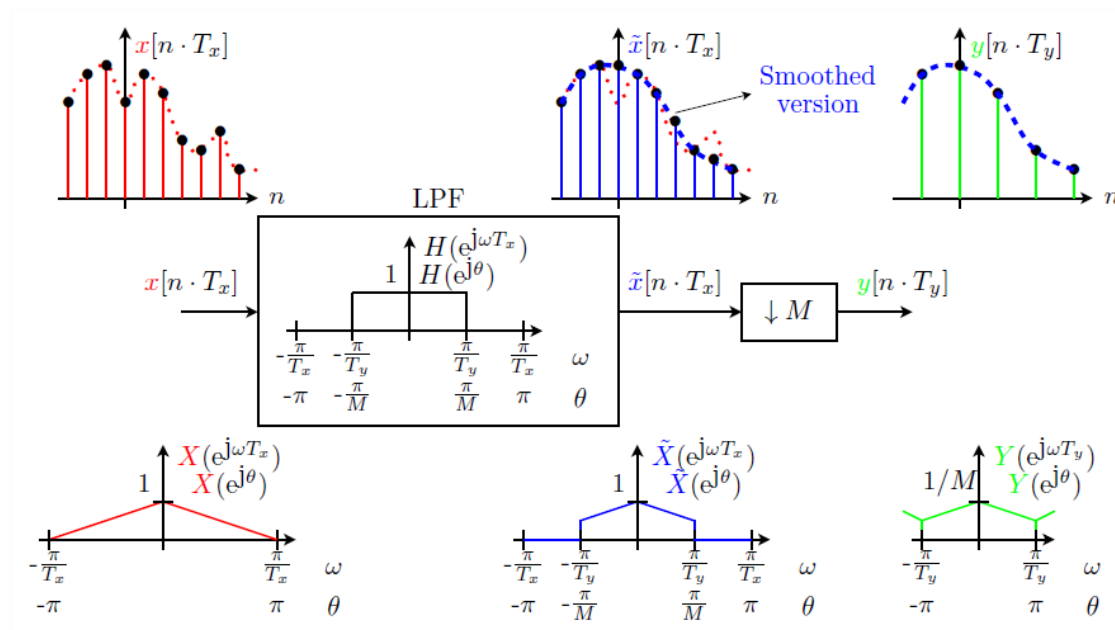
What happens if we change sample rate?





# Prevent aliasing artifacts when down-sampling

Decimator by integer factor  $M$ :

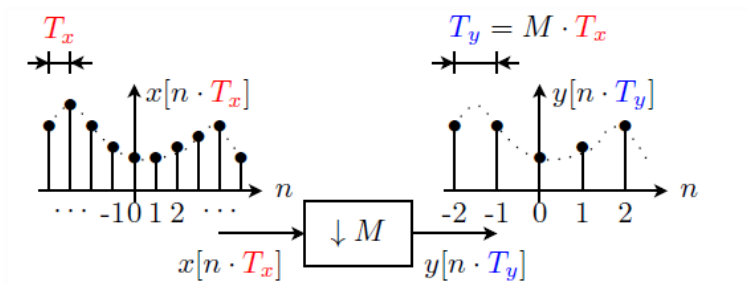


*Notes:*

- Prevent aliasing by LPF in front of SRD  $\Rightarrow$  Decimator
- SRD is not LTI

# Sample Rate Decrease

Sample Rate Decrease (SRD) by integer factor  $M$  (box  $\downarrow M$ ):



$$y[n \cdot T_y] = x[n \cdot (M \cdot T_x)]$$

$$X(e^{j\theta}) = \frac{1}{T_x} \sum_{k=-\infty}^{\infty} X_a\left(\frac{\theta}{T_x} - k \frac{2\pi}{T_x}\right)$$

$$Y(e^{j\theta}) = \frac{1}{T_y} \sum_{r=-\infty}^{\infty} X_a\left(\frac{\theta}{T_y} - r \frac{2\pi}{T_y}\right)$$

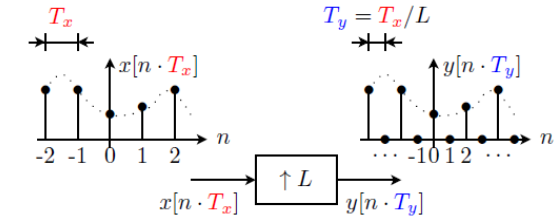
Split last sum with  $r = p + k \cdot M$  and use  $T_y = M \cdot T_x$

$$Y(e^{j\theta}) = \frac{1}{M} \sum_{p=0}^{M-1} \left\{ \frac{1}{T_x} \sum_{k=-\infty}^{\infty} X_a\left(\frac{(\theta - p \cdot 2\pi)}{M \cdot T_x} - k \cdot \frac{2\pi}{T_x}\right) \right\} \Rightarrow$$

$$Y(e^{j\theta}) = \frac{1}{M} \sum_{p=0}^{M-1} X(e^{j(\frac{\theta}{M} - p \cdot \frac{2\pi}{M})})$$

# Upsampling

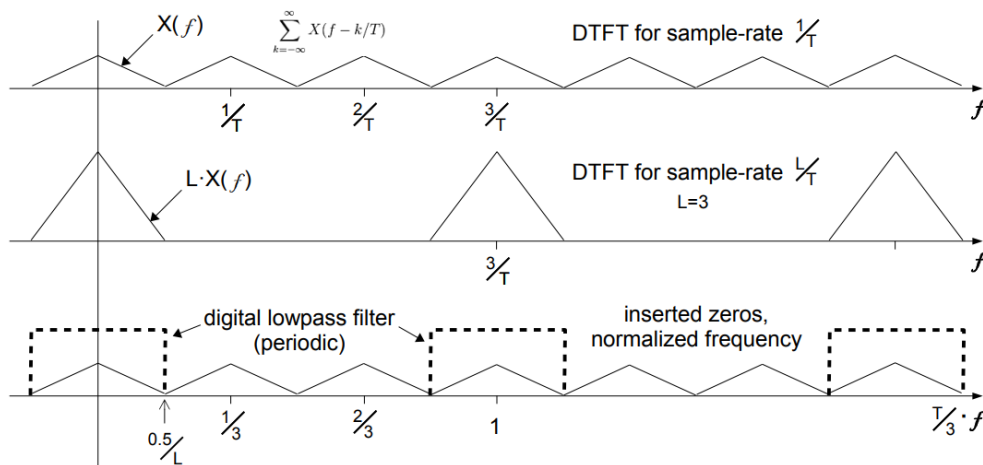
## Sample Rate Increase (SRI) by integer factor L



Algorithm:

1. Expansion: Create a sequence  $x_L[n]$ , comprising the original samples  $x[n]$  separated by  $L - 1$  zeros. A notation for this operation is:  $x_L[n] = x[n]_{\uparrow L}$
2. Interpolation: Smooth out the discontinuities with a lowpass filter, which replaces the zeros.

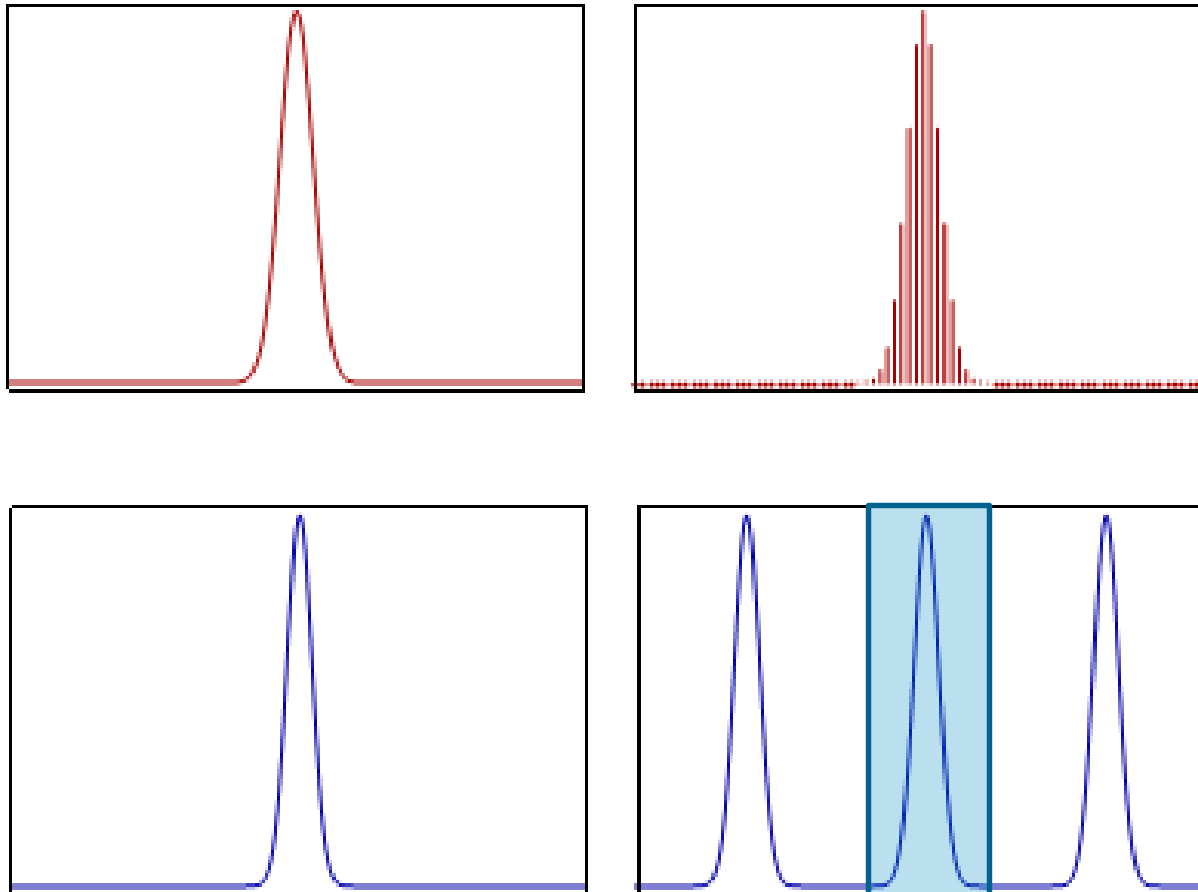
$$y[j + nL] = \sum_{k=0}^K x[n - k] \cdot h[j + kL], \quad j = 0, 1, \dots, L - 1,$$



[link](#)

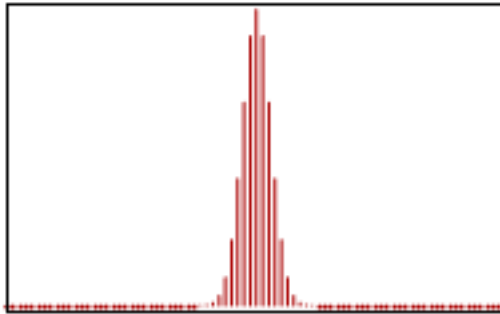
# Ideal interpolation

# Reconstruct continuous signal from samples

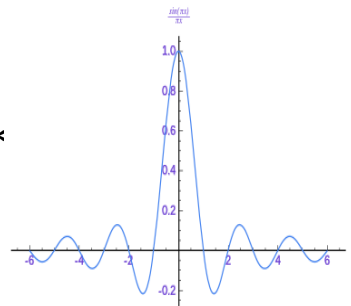


# Multiply frequency domain by rect

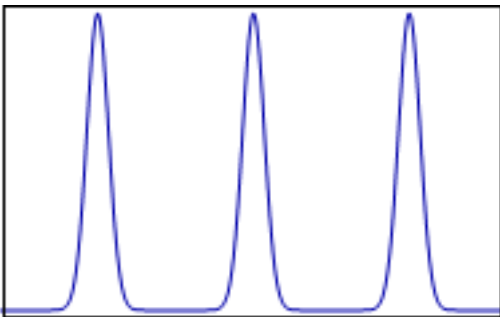
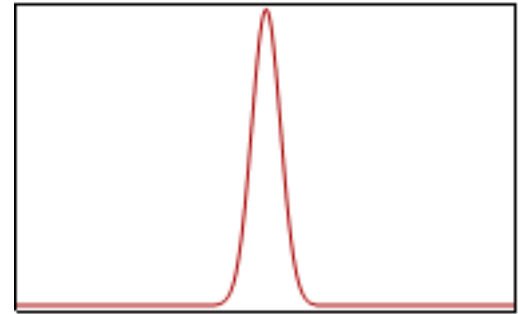
$$x(t) = \left( \sum_{n=-\infty}^{\infty} x[n] \cdot \delta(t - nT) \right) * \text{sinc}\left(\frac{t}{T}\right) = \sum_{n=-\infty}^{\infty} x[n] \cdot \text{sinc}\left(\frac{t - nT}{T}\right)$$



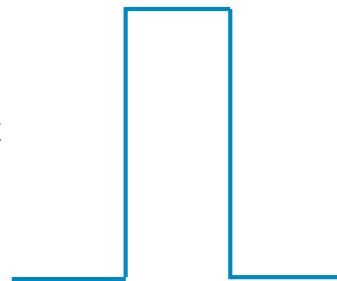
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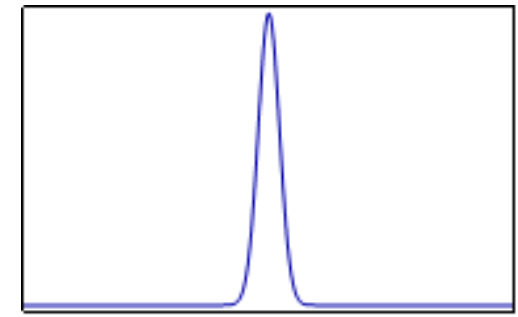
=



x



=



# Digital-to-Analog Conversion

Convert samples to pulses:  $x_s(t) = \sum_{n=-\infty}^{\infty} x[n] \delta(t - nT_s)$

Ideal LPF:  $H_r(\omega) = \begin{cases} T_s & |\omega| \leq \frac{\pi}{T_s} \\ 0 & |\omega| > \frac{\pi}{T_s} \end{cases} \quad \circ\text{---}\circ \quad h_r(t) = \frac{\sin(\frac{\pi}{T_s} \cdot t)}{\frac{\pi}{T_s} \cdot t}$

Filter  $x_s(t)$  to obtain  $x_a(t)$ :

$$\begin{aligned} x_a(t) &= x_s(t) * h_r(t) = \left( \sum_{n=-\infty}^{\infty} x[n] \delta(t - nT_s) \right) * h_r(t) \\ &= \sum_{n=-\infty}^{\infty} x[n] (\delta(t - nT_s) * h_r(t)) = \sum_{n=-\infty}^{\infty} x[n] \cdot h_r(t - nT_s) \end{aligned}$$

$\Rightarrow$  **Interpolation formula (time domain):**

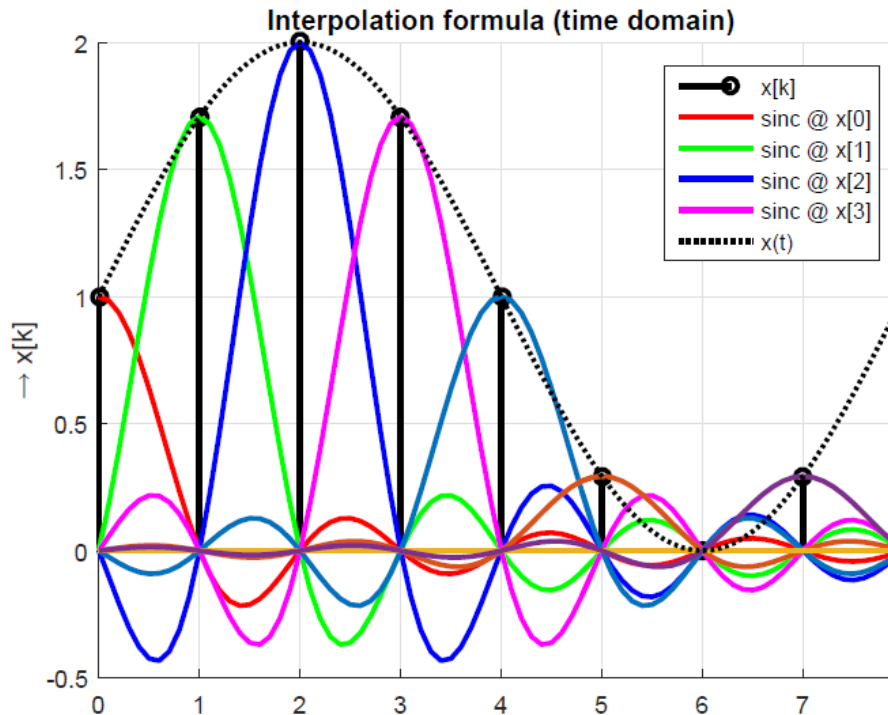
$$x_a(t) = \sum_{n=-\infty}^{\infty} x[n] \left( \frac{\sin(\frac{\pi}{T_s} \cdot (t - nT_s))}{\frac{\pi}{T_s} \cdot (t - nT_s)} \right)$$

Note: Refer to Shannon sampling theorem

# Digital-to-Analog Conversion

## Interpretation of interpolation formula (time domain):

$$x_a(t) = \sum_{n=-\infty}^{\infty} x[n] \left( \frac{\sin(\frac{\pi}{T_s} \cdot (t - nT_s))}{\frac{\pi}{T_s} \cdot (t - nT_s)} \right)$$

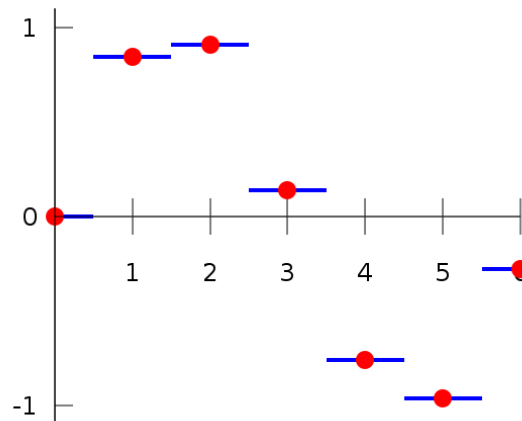




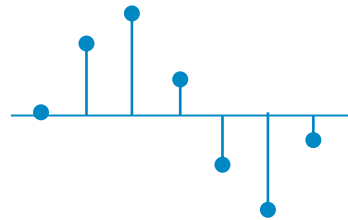
# Nearest neighbor, Linear, and Cubic interpolation

(Not LTI)

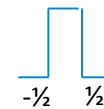
# Nearest Neighbor interpolation



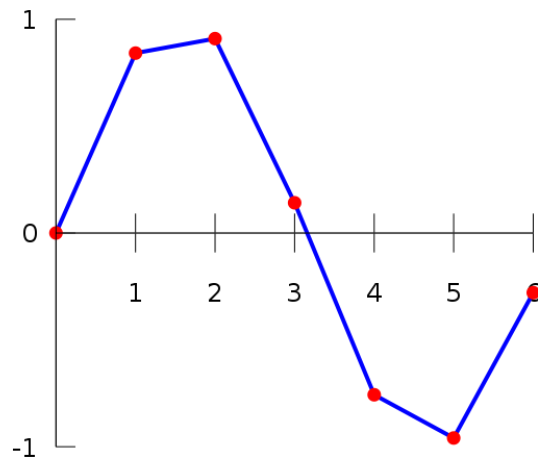
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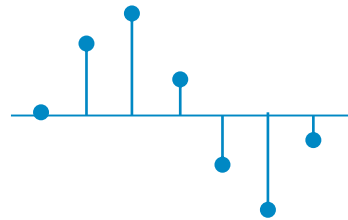
\*



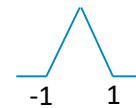
# Linear interpolation



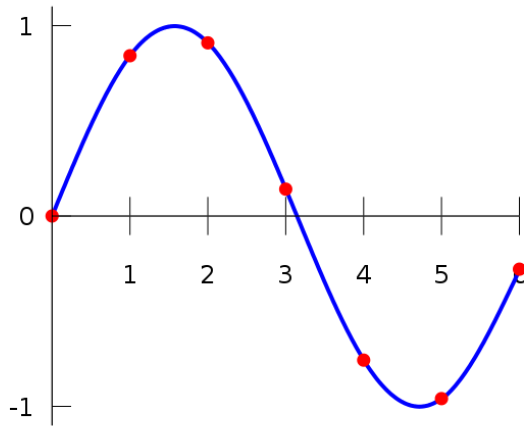
=



\*



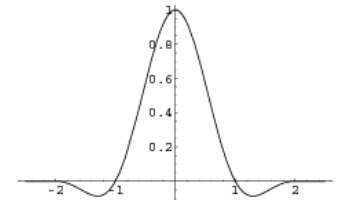
# Cubic interpolation



=

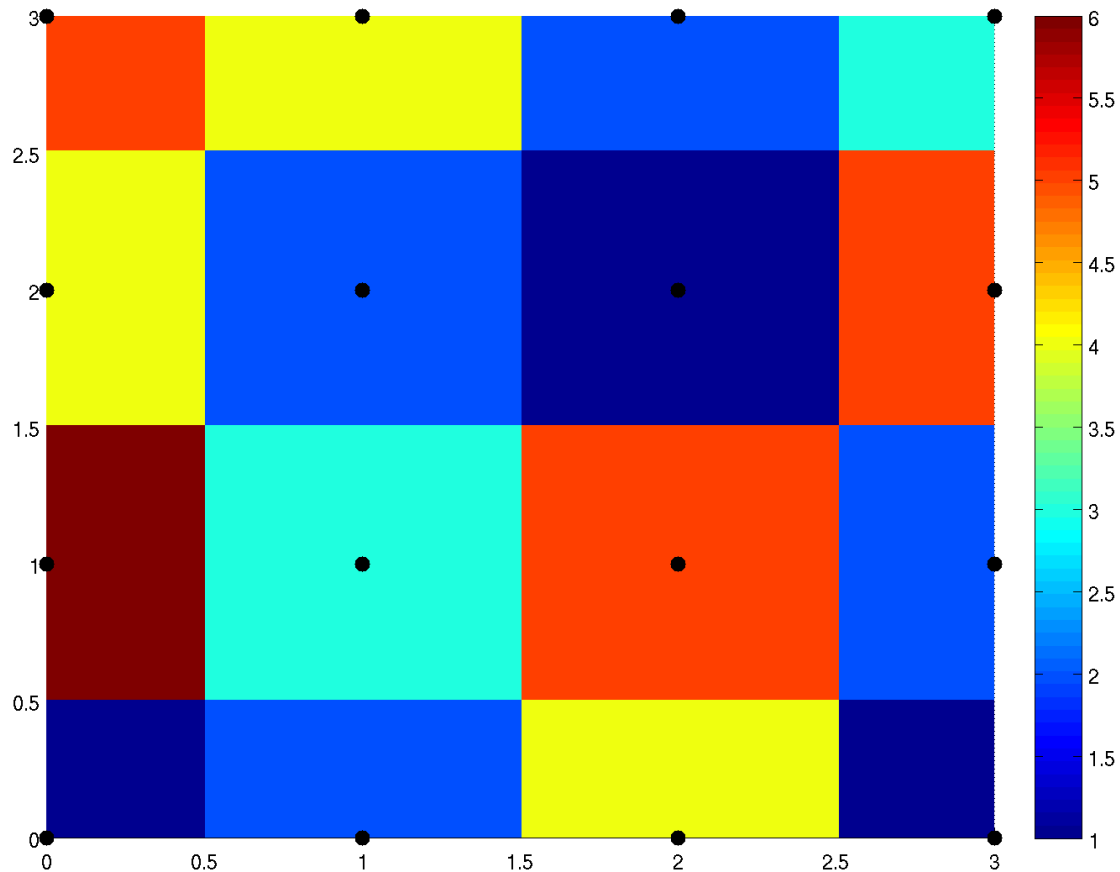


\*

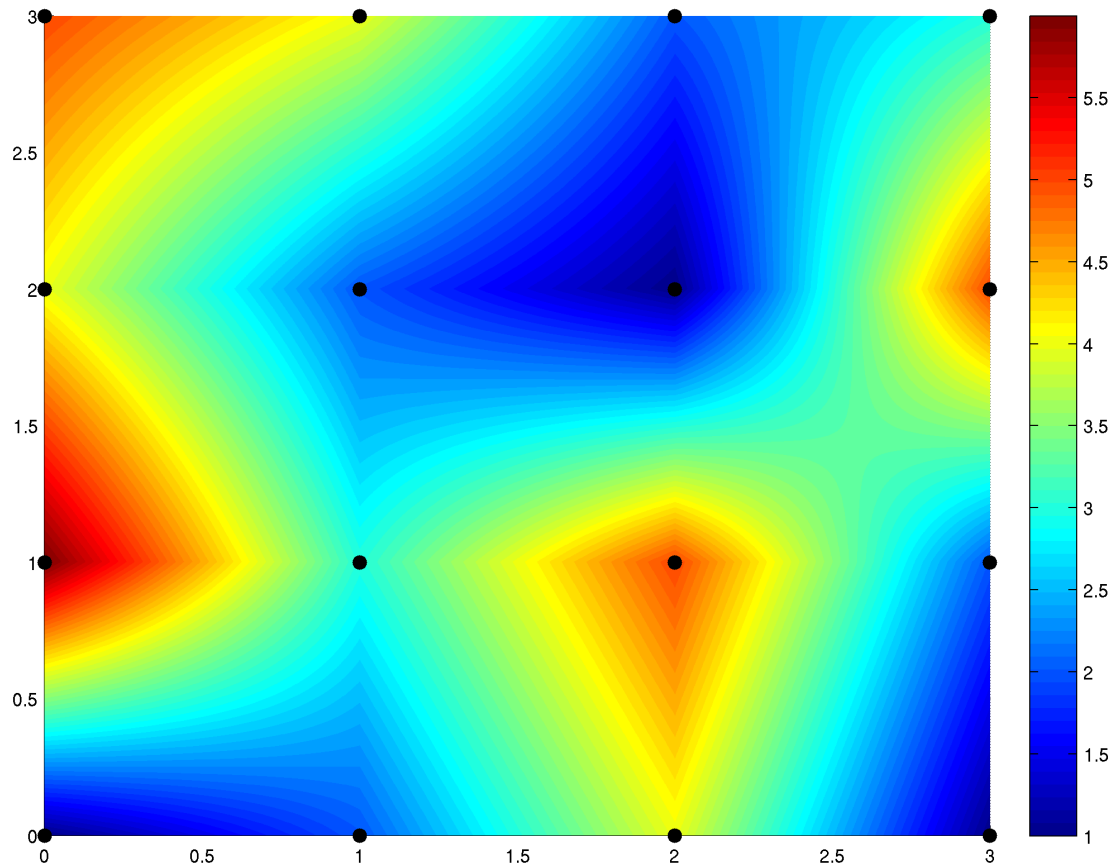


Lanczos kernel

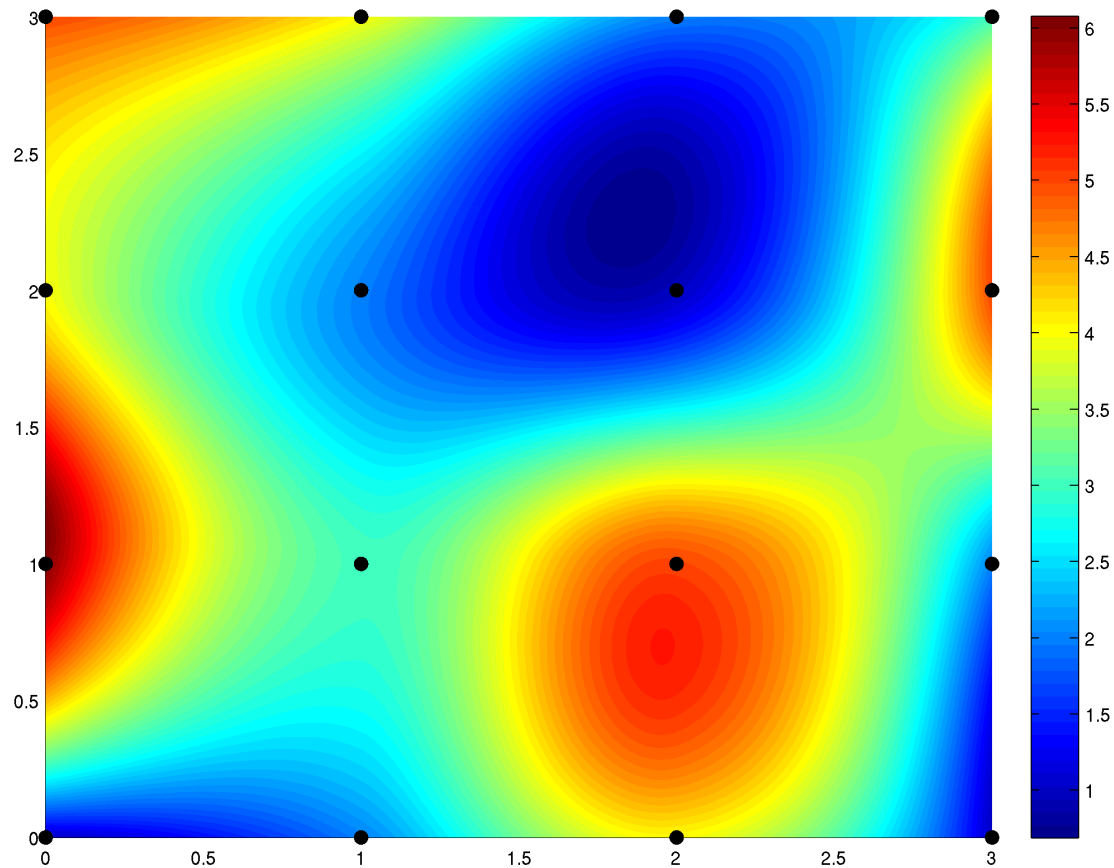
# 2D Nearest neighbor



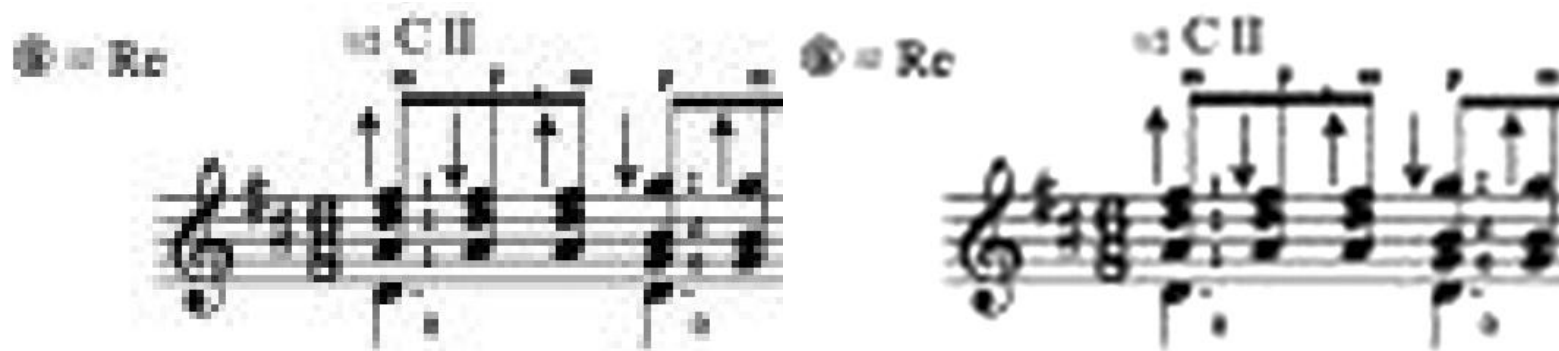
# 2D Linear



# 2D Cubic



# Nearest neighbor vs Cubic



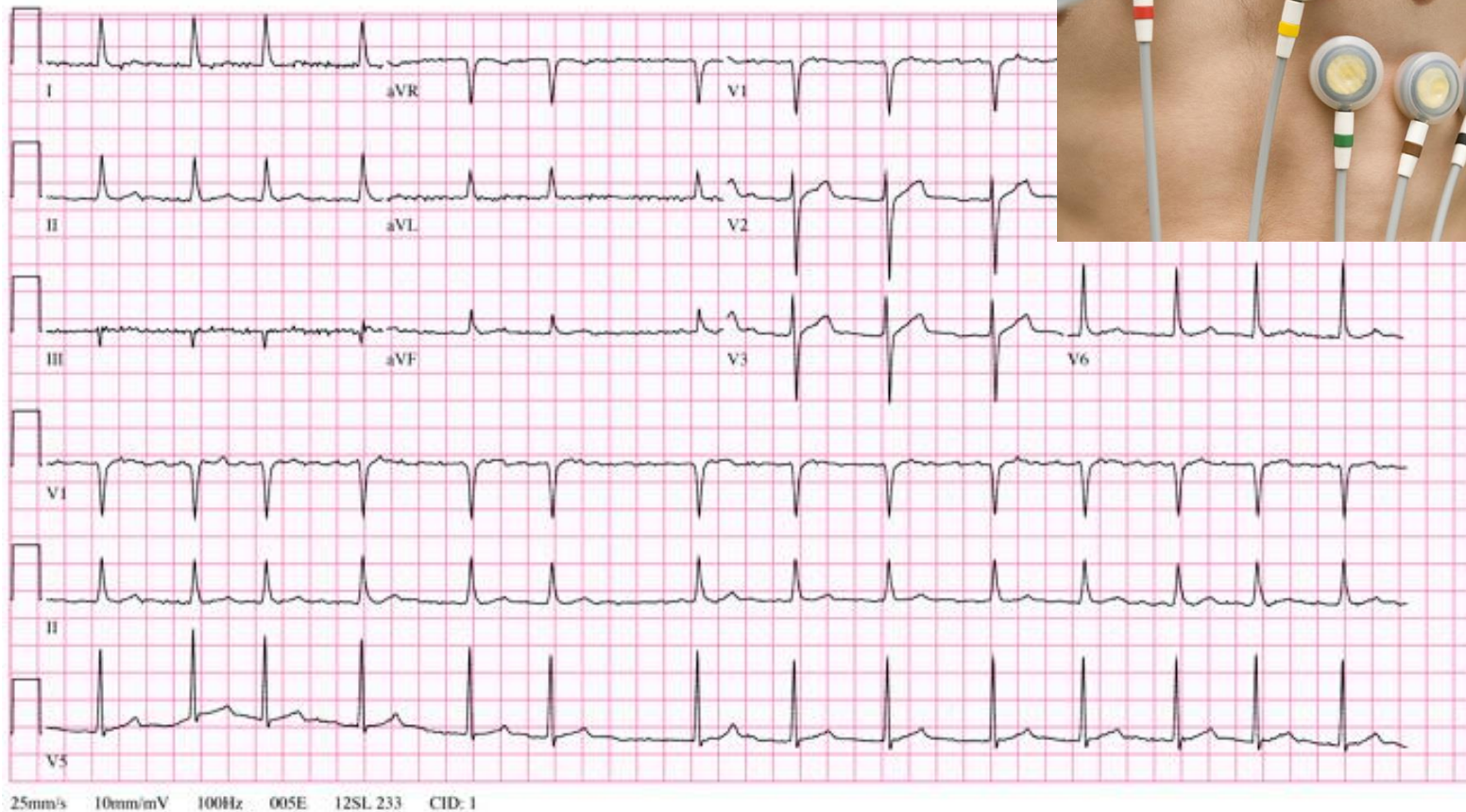
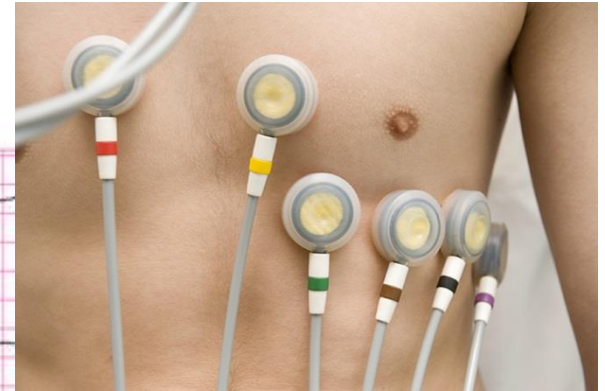


# Fast high quality interpolation

- Ideal interpolation: convolution with sinc
  - 😊 Ideal – high quality for bandwidth limited signals
  - 😞 Infinite support
  - 😞 Slow decay
- Nearest neighbor & linear interpolation
  - 😊 Simple to implement
  - 😊 Hardware acceleration
  - 😞 Low quality, smoothing effect
- Conclusion:
  - we would like best of both worlds
  - high quality (close as possible), fast interpolation

# Real world sampling

# Electrocardiogram - ECG

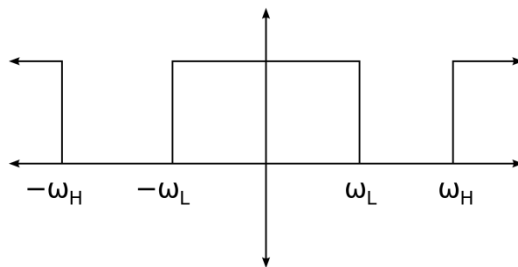


# 50 Hz or 60 Hz AC power interference



# How to remove the 50 or 60 Hz interference?

- Suppose we have a sampled ECG signal, sampled at e.g. 1000 Hz
- The discrete Fourier transform of the sampled signal will show the interference only around the 50 or 60 Hz mark
- A Band-stop filter can remove exactly that part

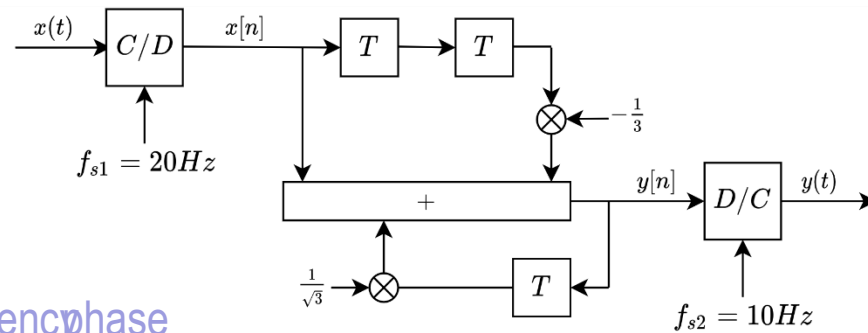


‘ideal’ band-stop filter

- In practice it may be preferable to smooth the edges, to prevent undesirable aliasing effects.

# Example

# Example

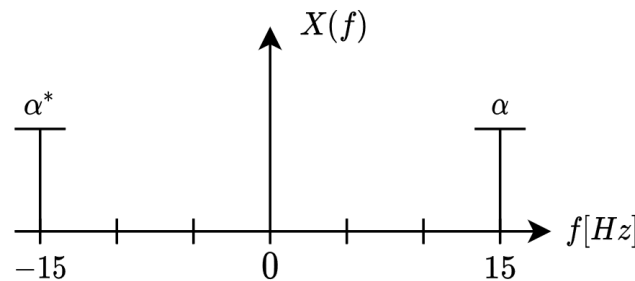


amplitude frequency phase

- \*  $x(t) = 3 \sin(30\pi t + \frac{\pi}{3})$
- \* Find  $y(t)$

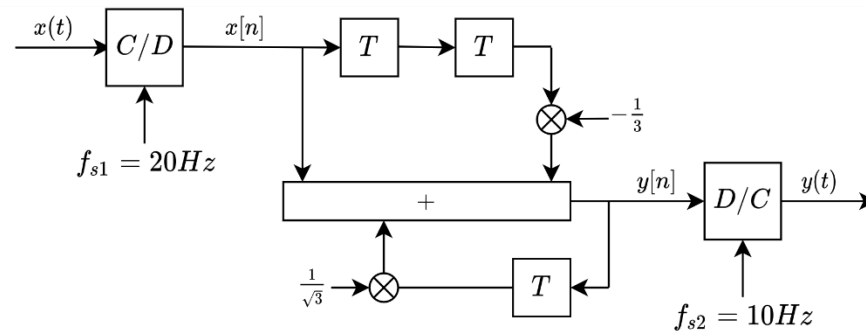
# Example

- \* We look at the spectral content of  $x(t)$
- \*  $x(t) = 3 \sin(30\pi t + \frac{\pi}{3}) = \frac{3}{2j} \cdot e^{j\frac{\pi}{3}} \cdot e^{j30\pi t} + \frac{-3}{2j} \cdot e^{-j\frac{\pi}{3}} \cdot e^{-j30\pi t}$
- \* Let us write  $\alpha = \frac{3}{2j} \cdot e^{j\frac{\pi}{3}}$  amplitude and phase
- \* Now  $x(t) = \alpha e^{j30\pi t} + \alpha^* e^{-j30\pi t} = \alpha e^{j2\pi \cdot 15t} + \alpha^* e^{-j2\pi \cdot 15t}$
- \* Now we know that the spectrum will have a delta pulse with weight  $\alpha$  at  $f = 15 \text{ Hz}$  and a delta pulse with weight  $\alpha^*$  at  $f = -15 \text{ Hz}$





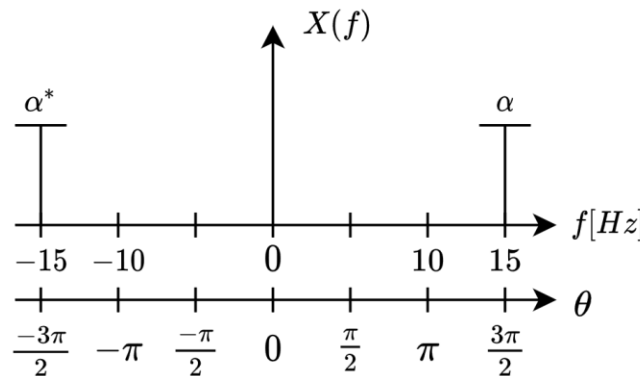
# Example



- \*  $x(t) = \alpha e^{j2\pi \cdot 15t} + \alpha^* e^{-j2\pi \cdot 15t}$
- \* Now we look at what happens when we convert this continuous-time signal to a discrete-time signal
- \* The C/D converter runs at  $f_{s1} = 20 \text{ Hz}$
- \* The fundamental interval will be between  $-10 \text{ Hz}$  and  $10 \text{ Hz}$
- \* Now we convert frequency to relative frequency through  $f_{s1}$
- \*  $\theta = \omega \cdot T_s = 2\pi \cdot 15 \cdot \frac{1}{20} = \frac{3\pi}{2}$
- \* Let us have a look at the spectrum again

# Example

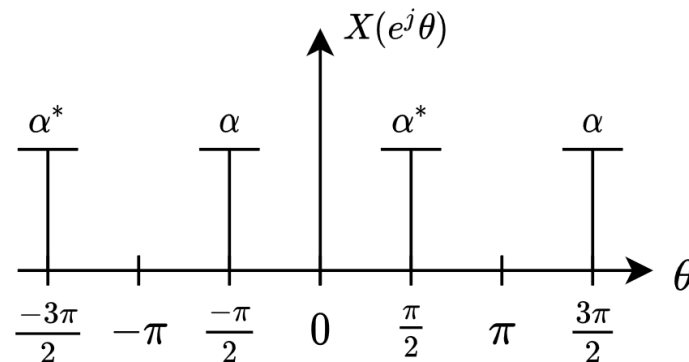
- \* We can observe that the spectral content is outside of the fundamental interval  $[-\pi, \pi]$
- \* When we sample, we convolve the time-domain signal with a pulse train, which causes the spectral content to repeat itself every  $2\pi$
- \* So the figure below will change



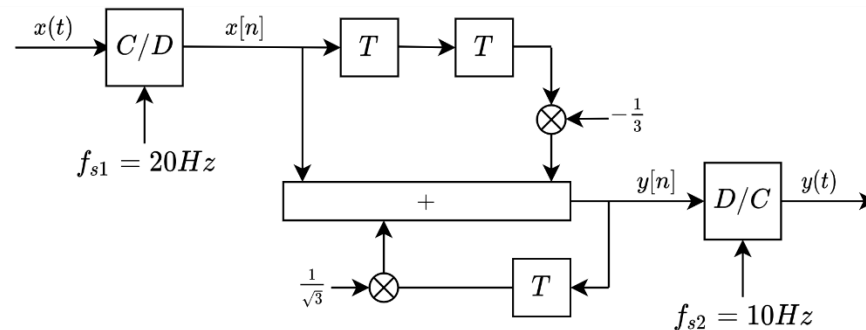
# Example

- \* By adding or subtracting  $2\pi$ , we find the pulses inside the fundamental interval
- \* We notice that the delta pulses crossed  $\theta = 0$ , which we see as a  $\pi$  phase shift
- \* We find our expression for  $x[n]$ :

$$x[n] = x_a(t)|_{t=n \cdot T_s} = 3 \sin\left(\frac{\pi}{2}n - \frac{2\pi}{3}\right)$$



# Example



- \* Now that we have found an expression for  $x[n]$ , we will equate it to  $y[n]$  through the difference equation of the LTI system above

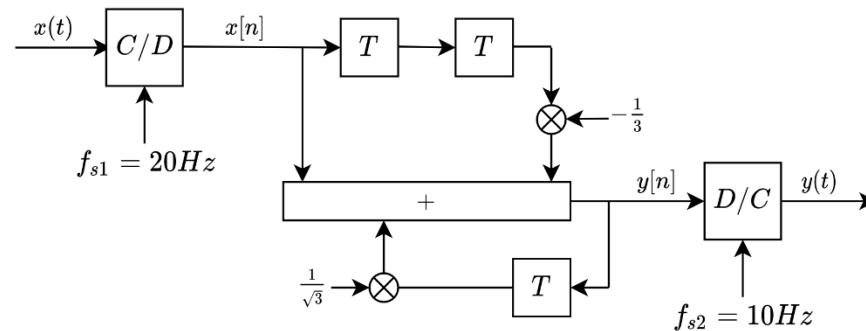
$$y[n] = x[n] - \frac{1}{3}x[n-2] + \frac{1}{\sqrt{3}}y[n-1]$$

- \* We solve this in frequency domain through the FTD:

$$Y(e^{j\theta}) = X(e^{j\theta}) - \frac{1}{3}e^{-j2\theta}X(e^{j\theta}) + \frac{1}{\sqrt{3}}e^{-j\theta}Y(e^{j\theta})$$

$$\Rightarrow Y(e^{j\theta})\left(1 - \frac{1}{\sqrt{3}}e^{-j\theta}\right) = X(e^{j\theta})\left(1 - \frac{1}{3}e^{-j2\theta}\right)$$

# Example



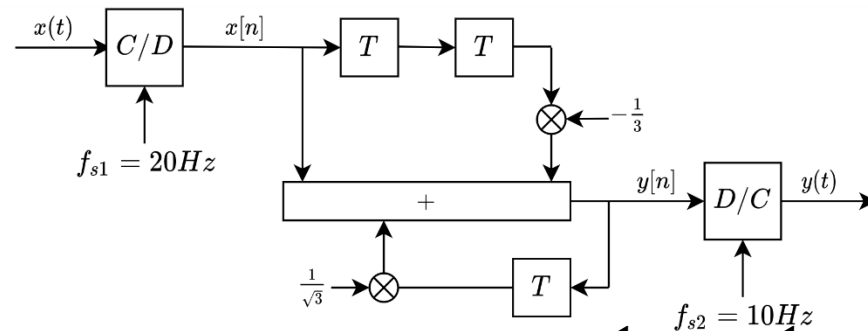
- \* We will find the frequency response  $H(e^{j\theta})$ :

$$Y(e^{j\theta}) \left( 1 - \frac{1}{\sqrt{3}} e^{-j\theta} \right) = X(e^{j\theta}) \left( 1 - \frac{1}{3} e^{-j2\theta} \right)$$

$$H(e^{j\theta}) = \frac{Y(e^{j\theta})}{X(e^{j\theta})} = \frac{1 - \frac{1}{3} e^{-j2\theta}}{1 - \frac{1}{\sqrt{3}} e^{-j\theta}}$$

- \* We know the system is LTI, so it will not change the frequency of our signal, but only the phase and magnitude
- \* Therefore, we evaluate the frequency response of our signal:  $H(e^{j\theta})|_{\theta=\pi/2}$

# Example



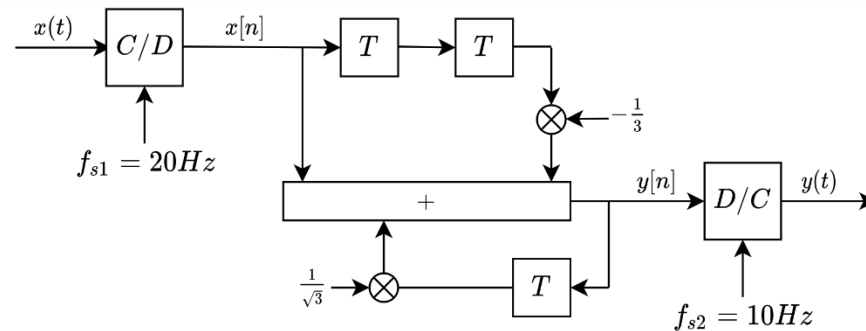
$$H(e^{j\theta}) \Big|_{\theta=\pi/2} = \frac{1 - \frac{1}{3}e^{-j\pi}}{1 - \frac{1}{\sqrt{3}}e^{-j\frac{\pi}{2}}} = \frac{1 + \frac{1}{3}}{1 + \frac{1}{\sqrt{3}}j} \cdot \frac{1 - \frac{1}{\sqrt{3}}j}{1 - \frac{1}{\sqrt{3}}j} = \frac{1\frac{1}{3} - 1\frac{1}{3\sqrt{3}}j}{1\frac{1}{3}} = 1 - \frac{1}{\sqrt{3}}j$$

$$\sqrt{1^2 + \left(\frac{-1}{\sqrt{3}}\right)^2} = \frac{2}{\sqrt{3}}, \quad \text{atan}\left(-\frac{1}{\sqrt{3}}/1\right) = -\frac{\pi}{6}, \quad \Rightarrow H(e^{j\theta}) \Big|_{\theta=\pi/2} = \frac{2}{\sqrt{3}}e^{-j\frac{\pi}{6}}$$

$$* \quad \left| H(e^{j\theta}) \Big|_{\theta=\frac{\pi}{2}} \right| = \frac{2}{\sqrt{3}}, \quad \angle \left\{ H(e^{j\theta}) \Big|_{\theta=\frac{\pi}{2}} \right\} = -\frac{\pi}{6}$$

- \* Now we know what the system does to the magnitude and phase for a frequency of  $\theta = \pi/2$

# Example



- \* Now we apply the effects of the frequency response to find  $y[n]$ :

$$y[n] = 3 \cdot \frac{2}{\sqrt{3}} \sin\left(\frac{\pi}{2}n - \frac{2\pi}{3} - \frac{\pi}{6}\right) = \frac{6}{\sqrt{3}} \sin\left(\frac{\pi}{2}n - \frac{5\pi}{6}\right)$$

- \* Now we convert this discrete-time signal back to a continuous-time signal through  $\omega = \theta f_{s2}$
- \*  $y(t) = \frac{6}{\sqrt{3}} \sin(5\pi t - \frac{5\pi}{6})$

# Conclusions



# Conclusions

- Basics: Fourier Transform, Convolution, ...
- Sampling theory
- Ideal interpolation
- Ideal upsampling
- Nearest neighbor, linear interpolation
- Generalized approximating interpolation

## Acknowledgements:

This lecture content is partially based on the slides by dr. Piet Sommen, and on content taken from Wikipedia and other public sources, indicated by the hyperlinks.

